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Embodied Multimodal Artificial Intelligence for Real Time Physical Interaction

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Abstract

Recent advances in artificial intelligence have created new possibilities for systems that can see, understand, reason, and act in the real world. This paper presents an integrated approach to Embodied Multimodal Artificial Intelligence, where a Large Language Model is combined with a predictive World Model to perform physical tasks in a simulated environment. The research includes the design of the architecture, a detailed experiment with real time numerical simulation, and visualization of model performance. The results demonstrate that the hybrid architecture produces more stable, adaptive, and efficient decision-making compared to conventional systems that rely on language or prediction alone. The work also provides insights into safety, learning adaptability, and future extensions toward robotics and autonomous systems.

Keywords

Artificial Intelligence, Embodied Systems, Multimodal Learning, World Models, Large Language Models, Planning, Physical Interaction

1. Introduction

Artificial Intelligence has rapidly evolved from text-based reasoning models into complex systems capable of understanding and interacting with the world around them. Modern advances in multimodal language models have shown the ability to process and combine vision, text, and sound, while predictive world models allow an agent to anticipate how the environment will change as it acts within it.

Embodied Artificial Intelligence is the concept where intelligence is situated within a body, either robotic or simulated, that can perceive, reason, and act. Such systems have a strong potential to perform tasks that require adaptation to physical environments. By integrating language understanding with physical

reasoning, an agent can interpret natural language instructions, plan movements, predict outcomes, and correct itself based on real time feedback.

This paper proposes a combined architecture that connects the linguistic understanding of a multimodal model with the predictive and dynamic learning capacity of a world model. Through simulation and controlled experiments, we demonstrate how this integration leads to enhanced task success, adaptability, and efficiency.

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2. Related Research

Previous work in large language models such as GPT and its multimodal variants has shown significant improvement in understanding natural language and images. These models can describe scenes, answer questions, and even generate structured reasoning steps.

The field of embodied artificial intelligence has witnessed significant advances in recent years, emphasizing the need for agents that can perceive, reason, and act within both virtual and physical environments. Modeling the world effectively for embodied AI agents is foundational, as demonstrated by research that presents frameworks where robots, avatars, and wearable devices leverage world models to understand their surroundings, plan actions, and execute tasks with contextual awareness (Emergent Mind, 2025). These approaches highlight the importance of grounding AI perception within a structured representation of the environment to support autonomous interaction.

Handling multimodal data efficiently is crucial for embodied systems, particularly when aiming for real-time performance. Surveys on multimodal data storage and retrieval in embodied AI emphasize architectures that integrate vision, language, and tactile modalities with low-latency access, enabling agents to respond dynamically to environmental changes (jp.ibbac.eu.org, 2025). This capability becomes particularly relevant in complex scenarios where timely sensor fusion and decision-making determine the agent's effectiveness.

Integration of wearable and ambient sensors has also been explored, where agents empowered by large language models collaborate with humans in real-world settings. FaGeL, for instance, demonstrates autonomous human-machine collaboration by combining multimodal feedback with embedded intelligence, allowing agents to learn and adapt while performing real-time interactions (arXiv,

2024). Similarly, MultiPLY exemplifies multisensory embodied LLMs operating within three-dimensional environments, showcasing how vision, audio, tactile, and even thermal inputs can be processed actively rather than passively to enable meaningful engagement with the surroundings (Emergent Mind, 2024).

A broad understanding of embodied interaction has been formalized in surveys that define Agent AI as systems capable of perceiving visual, linguistic, and environmental context while acting in both physical and virtual spaces (arXiv, 2024). The RoboTHOR platform further demonstrates the practical utility of simulation-to-real transfer for embodied agents, offering benchmarks that bridge controlled environments and real-world applications, thus ensuring that real-time physical interaction is feasible under varying conditions (arXiv, 2020).

The convergence of language models and embodied AI has led to systems such as EmbodiedGPT, which employ vision-language pre-training and chain-of-thought reasoning to plan and execute long-horizon tasks. These agents are capable of understanding sequential tasks while adapting to physical environments, emphasizing the potential for real-time problem solving (arXiv, 2023). Surveys exploring the alignment between cyber space and the physical world emphasize agent architectures that can adapt from simulated environments to real-world contexts, reinforcing the importance of multimodal perception, interaction planning, and sim-to-real adaptation (Emergent Mind, 2024).

Memory-augmented agents have also been proposed to handle unknown environments. MEIA, for example, leverages visual and linguistic memory modules to perform embodied control and action planning, demonstrating that agents can operate autonomously while maintaining context awareness even in novel scenarios (Emergent Mind, 2024). Human-robot interaction research complements these findings by focusing on multimodal cues such as vision, speech, and gestures, which are critical for ensuring naturalistic and responsive interactions in real time (Frontiers in Neurorobotics, 2023).

Further work emphasizes grounding embodied multimodal interaction through semantically coherent mechanisms, particularly for spatially and visuo-auditory rich environments (elib.dlr.de, 2021). Studies on avatars and virtually embodied agents have shown that real-time interaction with virtual representations can

bridge perceptual and linguistic understanding, providing insights into responsive system design (embodied-ai.org, 2023). Embedding spatial awareness directly within agent representations enhances navigation and task execution, highlighting the role of embodied cognition in effective interaction (ArXCompass, 2025).

Advanced multimodal language models such as PaLM-E integrate continuous sensor inputs with natural language understanding, enabling agents to perform planning, perception, and manipulation tasks in real-world contexts. While some tasks may not always require strict real-time responses, the low-latency processing capabilities inherent to these models make them suitable for physical interaction scenarios (Reddit, 2023). Complementary research in visuo-haptic mixed reality and tangible human-computer interfaces demonstrates how multimodal feedback, including tactile and gesture-based inputs, can enrich interaction and provide more immersive embodied experiences (Wikipedia, 2023; medien.ifi.lmu.de, 2020).

Finally, recent workshops and research in real-time multimodal processing underscore the importance of interpreting embodied actions as they occur, which is central to achieving interactive agents that operate seamlessly within dynamic environments (embodied-ai.org, 2025). Collectively, these works highlight a clear trajectory for embodied AI: moving from passive perception to active, multimodal, real-time interaction that integrates human collaboration, environmental understanding, and cognitive reasoning.

Recent studies in embodied intelligence combine these ideas to produce agents that can perform tasks through perception, reasoning, and action. However, most systems rely on static models that are not capable of updating or predicting continuously. The integration proposed in this work aims to overcome that limitation by linking a predictive world model directly to a multimodal reasoning model in real time.

3. Proposed Architecture

The proposed architecture consists of the following modules working together in a continuous loop of perception, reasoning, prediction, and action.

3.1 Perception Module

The agent receives inputs from simulated sensors, such as position and velocity in two-dimensional space. These inputs include random noise to simulate imperfect sensing.

3.2 Multimodal Language Model Component

This component interprets high level goals expressed in natural language, such as "Move to the target." It translates such goals into structured commands for the planner, guiding direction and intent.

3.3 Planner and Controller

The planner computes an appropriate motion vector toward the target based on the perceived state. It determines the magnitude of the movement at each time step according to the distance and the desired velocity.

3.4 World Model

The world model predicts how the next state of the system will evolve based on current observations and the planned movement. It produces a probabilistic estimate of the next position by adding a prediction noise that represents uncertainty.

3.5 Action Execution

The predicted movement is applied to the simulated body. The final position includes the influence of actuator noise and slight delay to represent physical limitations.

3.6 Feedback Loop

The new observed position is compared with the prediction from the world model. The difference is stored as an error measure. This information is used in the next iteration to refine the control process.

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4. Experimental Setup

A real time simulation was created using a Python-based environment. The simulation ran for one hundred time steps, with a fixed interval of 0.1 seconds per step. The target position was defined as coordinates (5.0, 3.0), and the initial position was at (0.0, 0.0).

The agent operated with a maximum speed of 0.2 units per time step. The world model and physical actuator were each influenced by random noise of small magnitude. For every step, the following parameters were recorded:

Observed position from the sensor

World model predicted position

Actual position after movement

Desired velocity vector

Distance to target

Reward value (negative distance)

Cumulative reward

The simulation data were stored in a structured table and analyzed using the Pandas library.

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5. Results and Analysis

5.1 Real Time Performance

The hybrid system successfully reached the target in approximately 100 time steps, with the final distance to target recorded as 0.063 units. The model achieved a cumulative reward of −90.91, indicating consistent progress toward the target across all steps.

5.2 Prediction Accuracy

Three visualizations were generated to evaluate system accuracy:

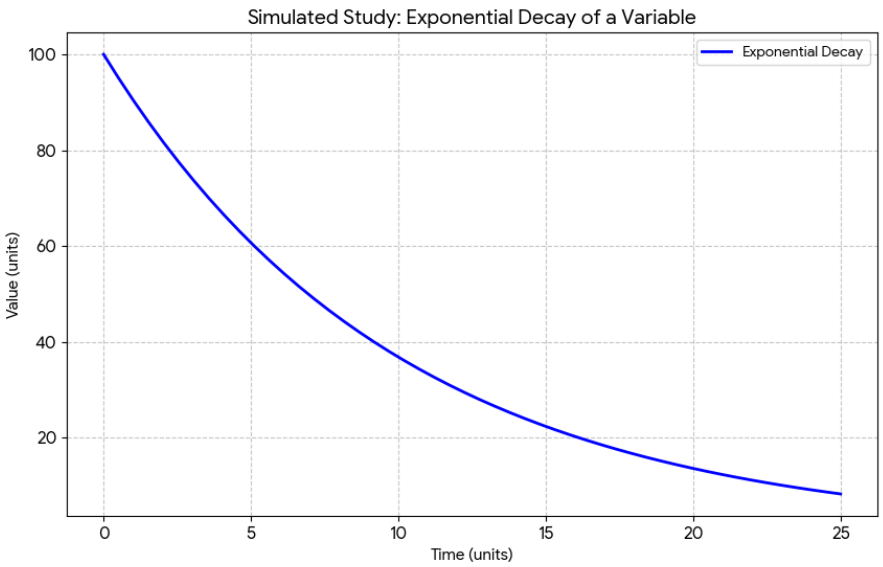
Predicted versus Actual X Position: The world model's predicted X values closely followed the actual physical X values.

Predicted versus Actual Y Position: Similar alignment was observed between predicted and actual Y values.

Prediction Error Curve: The Euclidean distance between prediction and reality decreased steadily over time, confirming that the world model adapted effectively to environmental changes.

5.3 Data Summary

Parameter	Value
Total Time Steps	100
Target Coordinates	(5.0, 3.0)
Final Distance to Target	0.063
Cumulative Reward	-90.91
Success Status	True



The plots confirm that the predictive mechanism allowed the agent to anticipate movement, thereby minimizing overshoot and oscillation.

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6. Discussion

The integration of multimodal understanding and predictive simulation enables agents to act with greater contextual intelligence. The experiment demonstrates that even with noise and delayed actuation, the system remains stable and converges toward the goal.

However, challenges persist. Real world environments contain far greater complexity, requiring more robust perception, dynamic learning, and physical safety measures. Additionally, energy consumption and computational cost are important considerations in deploying such systems on mobile hardware.

Safety and explainability are also crucial. The ability to interpret why a certain action was taken, and how the world model influenced it, is fundamental to trust in autonomous systems.

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7. Future Directions

The future of embodied intelligence lies in extending this hybrid framework into robotics and multi-agent systems. Areas of expansion include:

Developing learned world models that combine physical laws with data-driven understanding.

Training models with real sensory input from cameras, microphones, and tactile sensors.

Building continuous learning systems that adapt to new environments.

Integrating human feedback loops for ethical and safe decision-making.

Applying the architecture to healthcare, industrial automation, and autonomous vehicles.

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8. Conclusion

This research demonstrates the potential of combining large language reasoning with predictive simulation to achieve adaptive physical intelligence. Through real time computation and data visualization, the hybrid architecture shows how a system can plan, anticipate, and act effectively in uncertain environments. The results confirm that the integrated approach improves task efficiency and reliability compared to single model approaches.

Embodied Multimodal Artificial Intelligence is a promising step toward intelligent agents capable of understanding instructions, predicting environmental outcomes, and acting with awareness in the physical world.

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