A Vision-Grounded Cognitive Brain for Natural Language Control of a Robotic Arm

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Abstract

This paper presents a modular cognitive brain architecture for a robotic arm that enables natural language manipulation through vision-grounded reasoning. The proposed system integrates object perception, large language model (LLM) reasoning, symbolic planning, and short-term memory to safely convert user instructions into executable robot actions. Unlike end-to-end learning approaches, the architecture enforces physical constraints, safety rules, and determinism through explicit planning and memory mechanisms. Experimental deployment on a real robotic arm demonstrates reliable task execution, robust handling of ambiguity, and real-time interaction.

Keywords

Robotics, Cognitive Brain, Natural Language Processing, LLM, Vision-Grounded Reasoning, Symbolic Planning

1. Introduction

Robotic manipulation in human environments requires systems that can understand **natural language**, reason over **visual perception**, and execute **physically grounded actions**. While large language models (LLMs) have shown strong reasoning capabilities, directly coupling them to robotic actuators poses safety and reliability challenges.

This work introduces a **cognitive brain module** that bridges language understanding and robotic execution using a hybrid approach combining:

- Vision-grounded reasoning
- Symbolic planning
- Explicit memory and safety constraints

2. System Overview

The brain operates as an intermediate reasoning layer between perception and control. It receives:

1. Natural language commands from a human operator
2. Object detections from a vision subsystem

The output is a validated, low-level symbolic plan dispatched to the robot controller.

3. Cognitive Brain Architecture

3.1 Memory Module

A short-term memory module tracks:

- Whether the robot is holding an object
- Safety state (normal or emergency stop)

This prevents invalid actions such as multiple picks or unsafe motion sequences.

3.2 Vision-Grounded LLM Reasoning

The LLM interprets user commands under strict constraints:

- Only visible objects may be referenced
- Maximum of two action steps
- JSON-only structured output
- No hallucination of objects

The LLM outputs a high-level intent and action steps rather than direct motor commands.

3.3 Symbolic Planner

The planner converts abstract steps into executable robot actions:

- Object selection based on distance (nearest/farthest)
- Relative spatial placement (left/right/front)
- Deterministic action templates

This ensures interpretability and reproducibility.

3.4 Safety Enforcement

Before execution, all LLM decisions are validated against:

- Current memory state
- Vision confidence thresholds
- Action legality rules

Unsafe or ambiguous commands result in conversational feedback instead of execution.

4. Implementation Details

The system is implemented in Python using a modular architecture. Communication between subsystems occurs via REST APIs, enabling distributed deployment across edge devices such as Raspberry Pi and robot controllers.

5. Experimental Results

The brain module was evaluated on real-world manipulation tasks including pick-and-place and handover actions. The system successfully:

- Resolved ambiguous commands using vision context
- Prevented unsafe operations
- Maintained consistent execution latency under real-time constraints

6. Discussion

Compared to end-to-end approaches, the proposed architecture provides:

- Improved safety
- Better explainability
- Easier debugging and extension

The hybrid LLM-symbolic design offers a practical path toward deployable language-driven robots.

7. Conclusion

This paper demonstrates a vision-grounded cognitive brain that enables reliable natural language control of a robotic arm. By combining LLM reasoning with explicit memory and symbolic planning, the system achieves safe, interpretable, and real-time manipulation. Future work will extend the memory horizon and incorporate multi-step task learning.

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