Fault tolerant and long-term robot policies from natural language instructions

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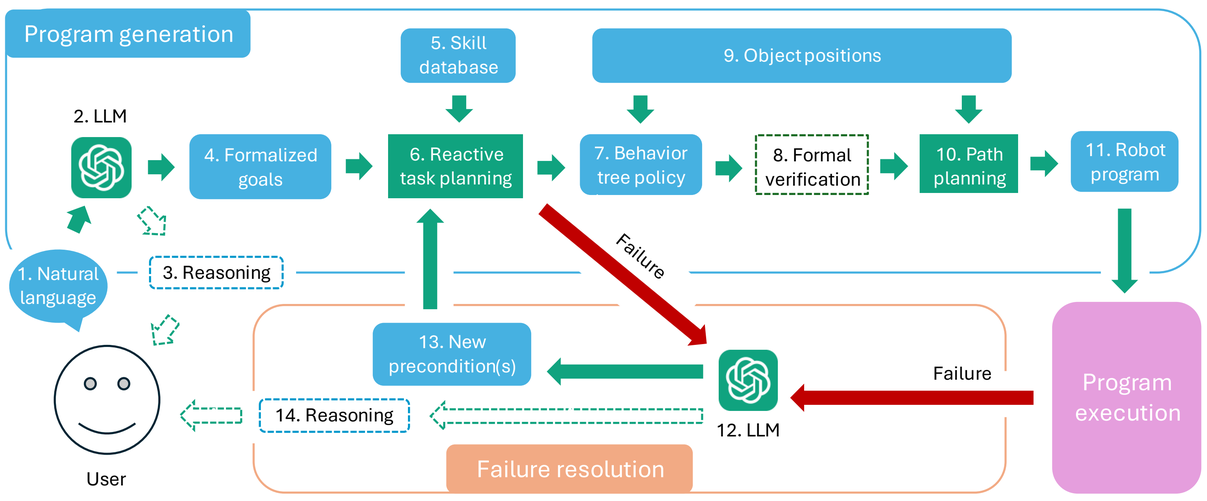
Overall motivation & research goals

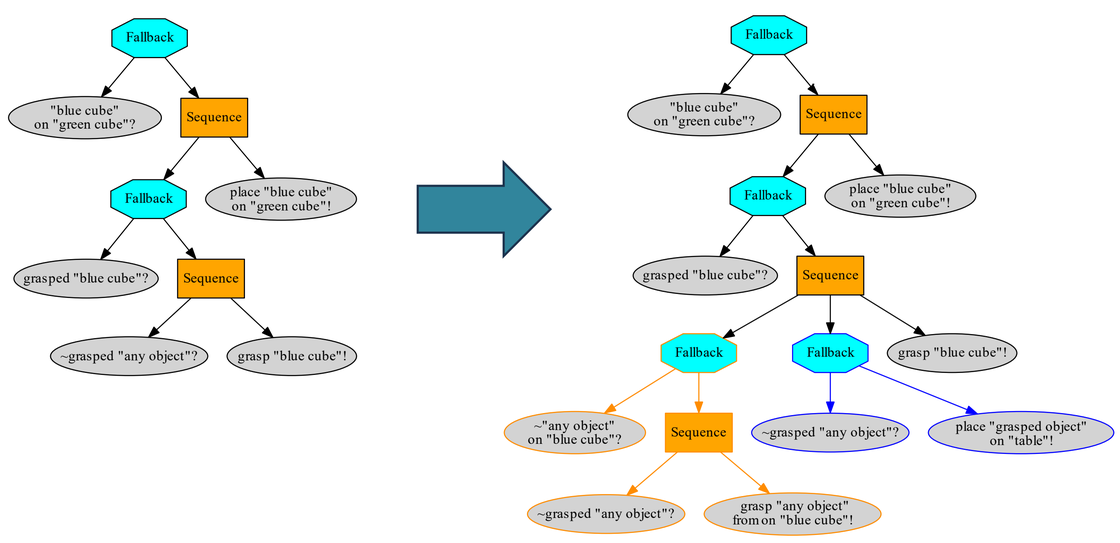
Industrial robots can solve tasks in controlled environments, but modern applications require robots able to operate also in **unpredictable surroundings**. An increasingly popular reactive policy architecture in robotics is **Behavior Trees (BTs)** [1] but as with other architectures, programming time drives cost and limits flexibility. We investigate methods for collaborative robots to **plan** and **learn** interpretable control architectures such as Behavior Trees and look at combinations of many different methods such as **Genetic Programming** [2, 3, 5], **Planning** [3, 4, 7, 8], **Learning from Demonstration** [4, 5], **Bayesian Optimization** [6] and **language models** [7, 8].

Highlight method, BETR-XP-LLM

We propose the method BEhavior TRee eXPansion with Large Language Models (BETR-XP-LLM)[7] to dynamically and automatically expand and configure Behavior Trees as policies for robot control. The method utilizes an LLM to **resolve errors outside the task planner's capabilities**, both during planning and execution. We show that the method can solve a variety of tasks and failures and update the policy to handle similar problems in the future.



Method overview



Example of BT before(left) and after(right) failure resolution

Experiments

- We tested goal inference on a set of 100 tasks of varying difficulty from LLM-OBTEA [9].
- We successfully tested the failure resolution capabilities of the method on 10 diverse tasks for identifying missing preconditions.
- We implemented our method on an ABB YuMi system for a subset of the tasks and successfully executed them to show our methods validity in a real setting.

Goal inference results

Difficulty	0F GPT-3.5	5F GPT-3.5	0F GPT4	Ours
Easy	84.7%	90.7%	90.0%	100.0%
Medium	76.7%	82.0%	86.7%	100.0%
Hard	59.0%	65.0%	85.5%	97.0%

TABLE 1: Prompt results for varying levels of difficulty. All columns except the one titled "Ours" use LLM-OBTEAs original prompt. Methods denoted "0F" use no reflective feedback while "5F" means up to five rounds of reflective feedback. Ours is using GPT-4-1106 and no reflective feedback. Our method achieves an almost perfect score while LLM-OBTEA struggles also with up to five rounds of reflective feedback.

Difficulty	Ours	No desc.	No obj spec.	Orig ex	CoT
Easy	100.0%	100.0%	96.7%	91.3%	98.0%
Medium	100.0%	93.3%	90.0%	93.3%	96.0%
Hard	97.0%	88.5%	86.0%	91.0%	93.5%

TABLE 2: Prompt ablations. "Ours" is our complete improved prompt. "No desc" has no condition descriptions. "No obj spec" has no specification to only use listed objects. "Orig ex" has the original examples. "CoT" uses a chain of thought prompt with reasoning before the answer.

Future work

- It would be interesting to study whether the combination with the planner can be used to resolve ambiguous instructions without extended communication with the user, by for example ruling out branches that the planner deems unsolvable.
- A case we did not study is when the skill library is missing the necessary actions to solve the task. Utilizing the LLM to create those actions from lower-level primitives is another interesting prospect.

References

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