

# Make a Donut 🍩 : Language-Guided Hierarchical EMD-Space Planning for Zero-Shot Deformable Object Manipulation

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## Problems with Deformable Manipulation

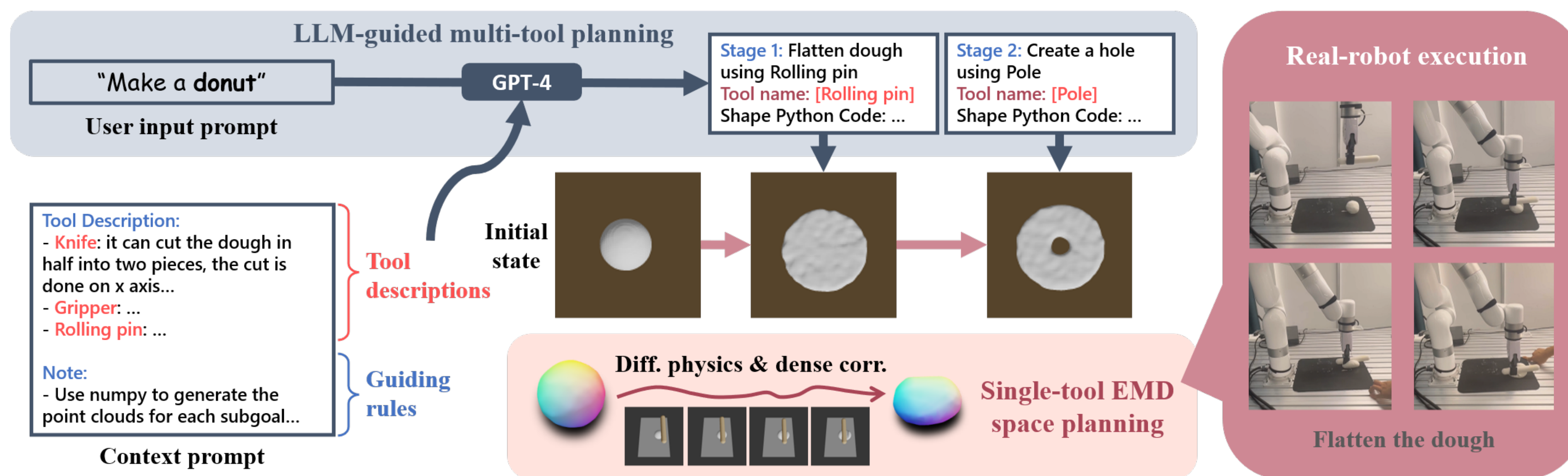


- How to generate good paths, with infinite degrees of freedom
- In general, long-horizon task planning is non-trivial

Check out our project website



## Method Overview



### Top level: Multi-Tool Selection with LLM Guidance

We ask the LLM to output the following items:

- A one-line explanation of what this step is doing
- Name of the tool to be used.
- Python code to generate target point clouds
- Variable names for the input and output.
- Location of each piece in a dictionary format with a variable name as the key
- Volume of each piece is also in a dictionary format with a variable name as the key

Additional guidelines in the prompt:

- Volume preserving
- Chain of reasoning

volume changes ↓

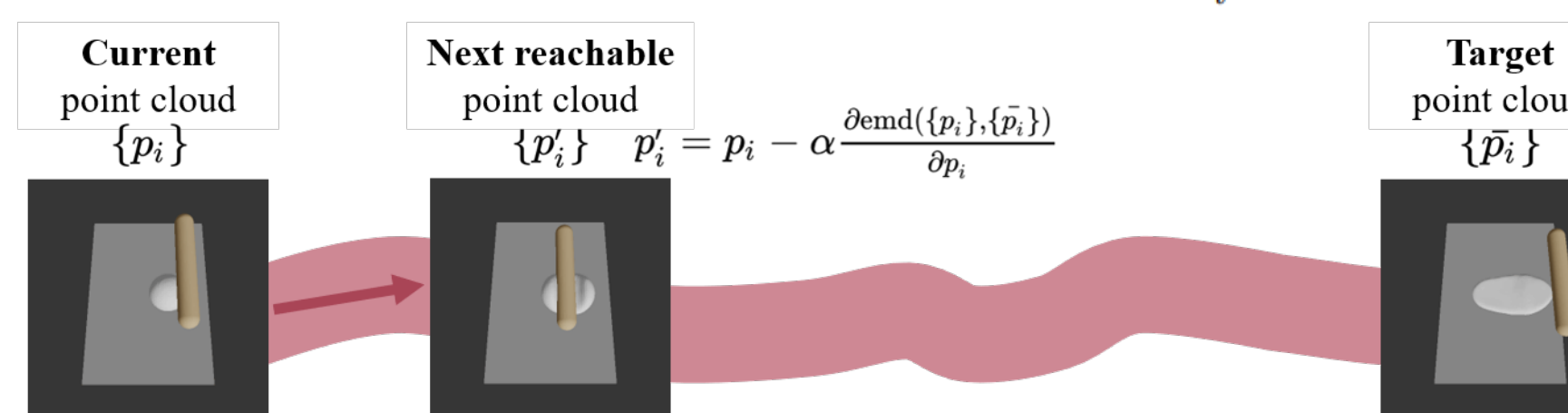
	Donut ↓	Baguette ↓	TwoPancakes ↓
w/o Volume Preserving and Chain Reasoning	73.9%	42.5%	65.0%
Ours	9.8%	38.9%	0.0%

### Bottom level: Single-Tool Planning in the EMD Space

DiffPhysics-P2P: Decide the next subgoal with

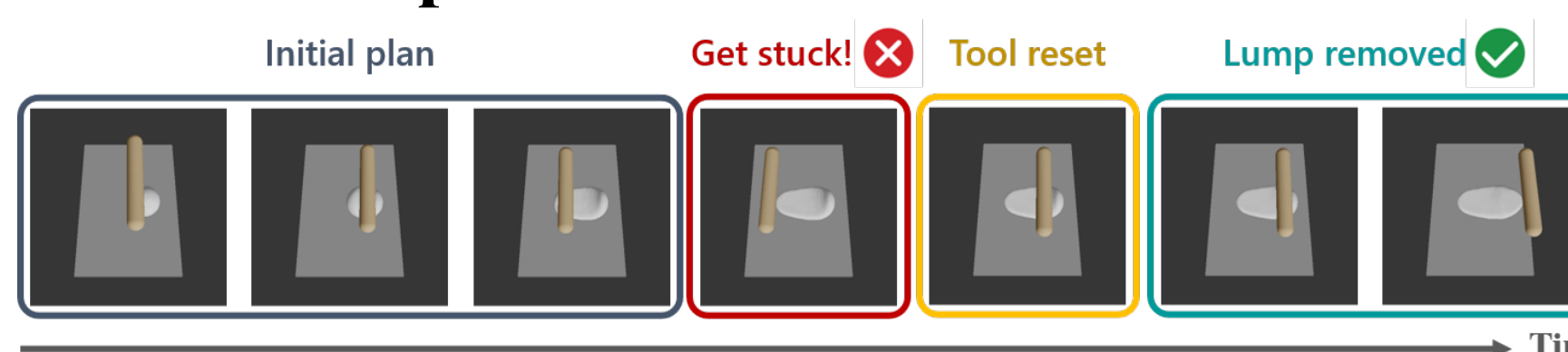
$$\mathbf{p}'_i = \mathbf{p}_i - \alpha \cdot \frac{\partial \text{emd}(\{\mathbf{p}_i\}, \{\bar{\mathbf{p}}_i\})}{\partial \mathbf{p}_i}$$

Initial position selection  $\mathbf{x}^* = \arg \max_{\mathbf{x}} \sum_i \frac{\|\mathbf{p}'_i - \mathbf{p}_i\|_1}{\text{sdf}_{\mathbf{x}}(\mathbf{p}_i) + \delta}$



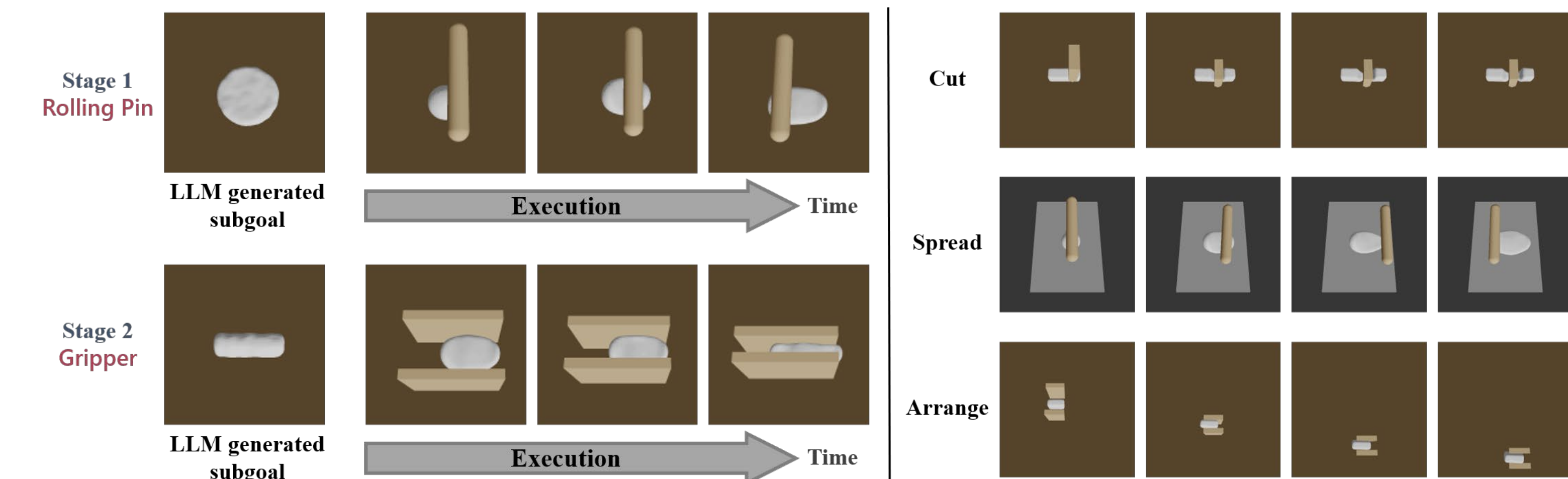
Diff. physics from dense corr.  $L = \sum_i \|\mathbf{p}'_i - \mathbf{p}_i\|_1$

Tool reset upon failures

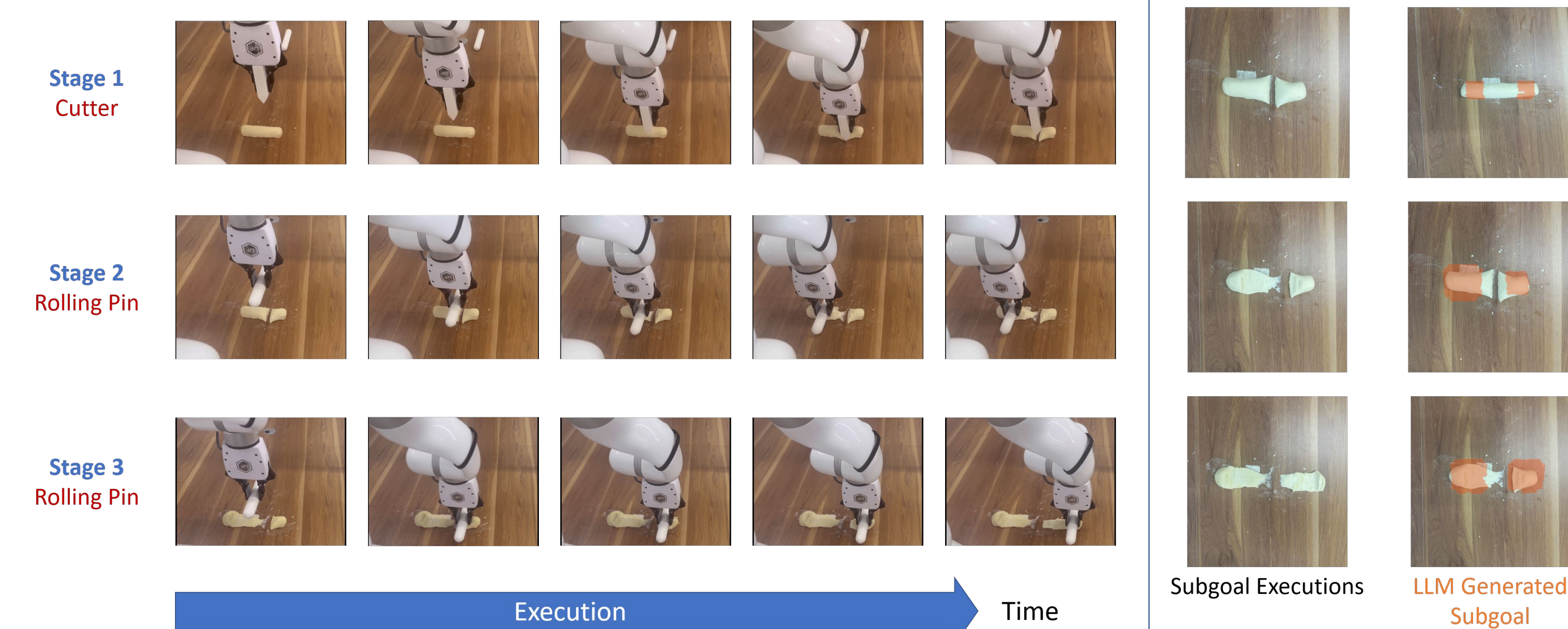


## Experimental Results

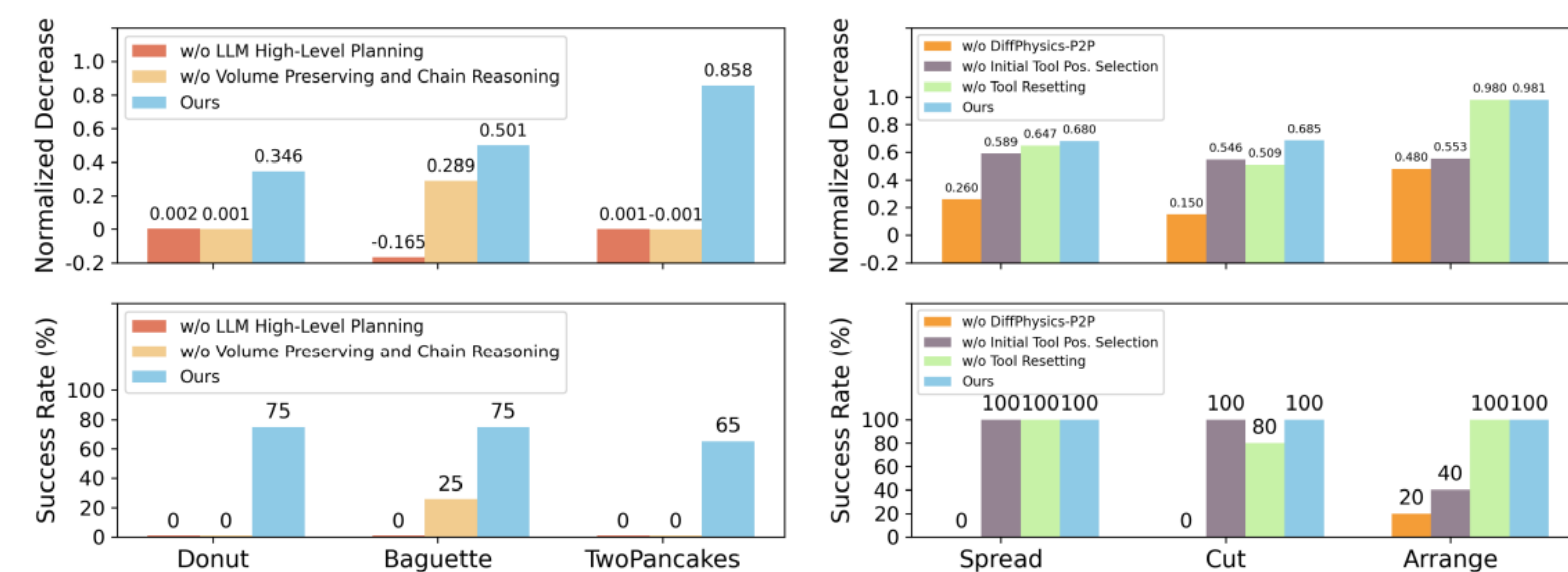
### Simulation Results



### Real-robot Results



### Ablation Studies



(a) Ablation results for multiple-tool experiments.

(b) Ablation results for single-tool experiments.