Learning Fine-Grained Bimanual Manipulation with Low-Cost Hardware

RSS 2023

양현서

July 12, 2024

About

- Author: Tony Z. Zhao, Vikash Kumar, Sergey Levine, Chelsea Finn

- Conference: RSS 2023

Motivation

- **Fine manipulation tasks** such as
  - threading cable ties
  - slotting a battery

Motivation

- **Fine manipulation tasks** such as
  - threading cable ties
  - slotting a battery

- **Requires**
  - precision
  - careful coordination of contact forces
  - closed-loop visual feedback

Low cost and imprecise hardware for fine manipulation tasks

Suggestion

Low-cost system that performs end-to-end **imitation learning** directly from real demonstrations, collected with a custom teleoperation interface

Introduction

- Fine manipulation tasks require **precision and coordination**

Introduction

- Fine manipulation tasks require **precision and coordination**
- Current systems are **expensive and complex**

Introduction

- Fine manipulation tasks require **precision and coordination**
- Current systems are **expensive and complex**
- Goal: Develop a low-cost, effective system for bimanual manipulation

Introduction

- Fine manipulation tasks require **precision and coordination**
- Current systems are **expensive and complex**
- Goal: Develop a low-cost, effective system for bimanual manipulation
- Key contributions:
  - **Low-cost** hardware setup
  - Novel imitation learning algorithm **(ACT)**
  - Successful demonstration on various tasks

System Design - Low-cost hardware

- ViperX 6-DoF robot arms
- 3D printed “see-through” fingers, gripping tape
- **Cost: <$20k**

System Design - Design principles

- Versatile

System Design - Design principles

- Versatile
- User-friendly

System Design - Design principles

- Versatile
- User-friendly
- Repairable

System Design - Design principles

- Versatile
- User-friendly
- Repairable
- Easy-to-build

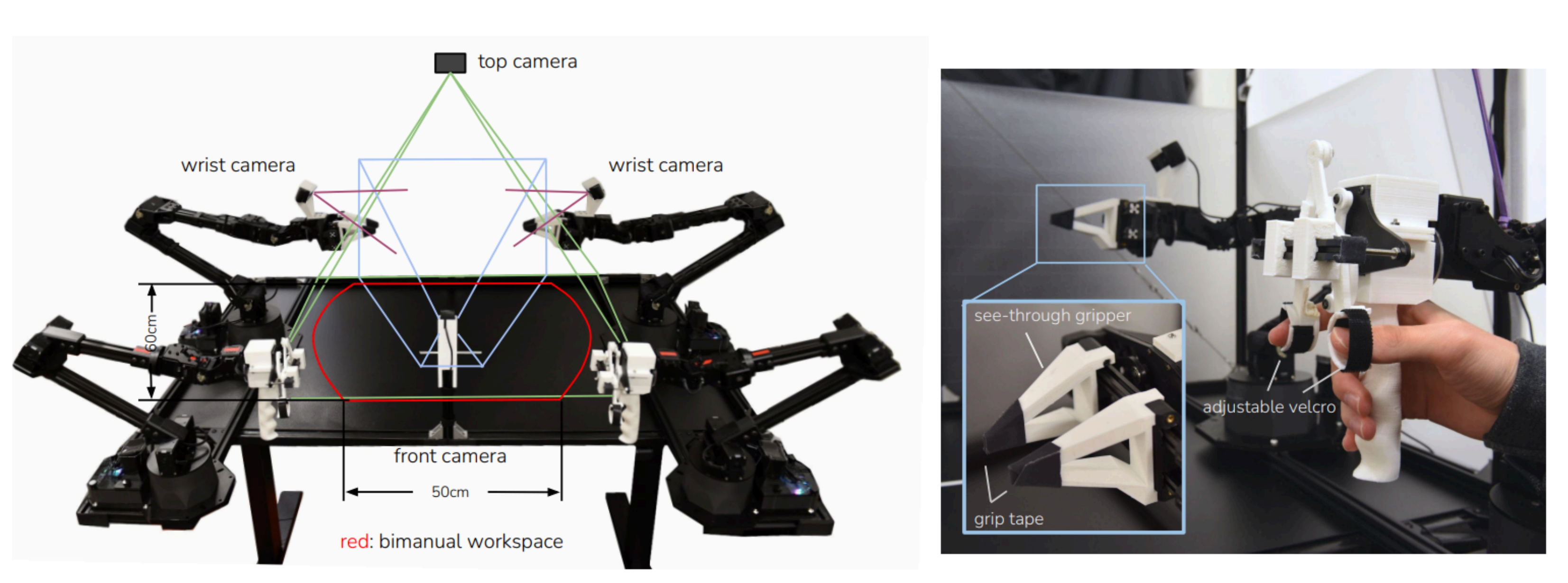
System Design - Design principles - Teleoperation setup

- Joint-space mapping for control

- High-frequency control (50Hz)

Joint space mapping for control

- Directly maps "Leader" joint angles to "Follower" joint angles
- Solves IK failing problem



Imitation Learning Algorithm

Imitation Learning Algorithm

- **Challenges**:
  - Compounding errors in policy
  - Non-stationary human demonstrations

Imitation Learning Algorithm

- **Challenges**:
  - Compounding errors in policy
  - Non-stationary human demonstrations

- **Solution: Action Chunking with Transformers (ACT)**:
  - Predicts sequences of actions (chunks)
  - Reduces effective horizon of tasks
  - Uses temporal ensembling for smoothness

Training ACT on a New Task

- Record leader joint positions as actions

Training ACT on a New Task

- Record leader joint positions as actions
- Observations: follower joint positions, 4 camera feeds

Training ACT on a New Task

- Record leader joint positions as actions
- Observations: follower joint positions, 4 camera feeds
- Train ACT: predict future actions from observations

Training ACT on a New Task

- Record leader joint positions as actions
- Observations: follower joint positions, 4 camera feeds
- Train ACT: predict future actions from observations
- Test: use policy with lowest validation loss

Training ACT on a New Task

- Record leader joint positions as actions
- Observations: follower joint positions, 4 camera feeds
- Train ACT: predict future actions from observations
- Test: use policy with lowest validation loss
- **Challenge: Compounding errors**

Action Chunking

- **Groups individual actions into units** for efficient storage and execution

Action Chunking

- **Groups individual actions into units** for efficient storage and execution

- Reduces the **effective horizon** of long trajectories

Action Chunking

- **Groups individual actions into units** for efficient storage and execution

- Reduces the **effective horizon** of long trajectories

- Every k steps, the agent receives an observation and generates k actions

Action Chunking

- **Groups individual actions into units** for efficient storage and execution

- Reduces the **effective horizon** of long trajectories

- Every k steps, the agent receives an observation and generates k actions

- Mitigates issues with non-stationary demonstrations

Action Chunking

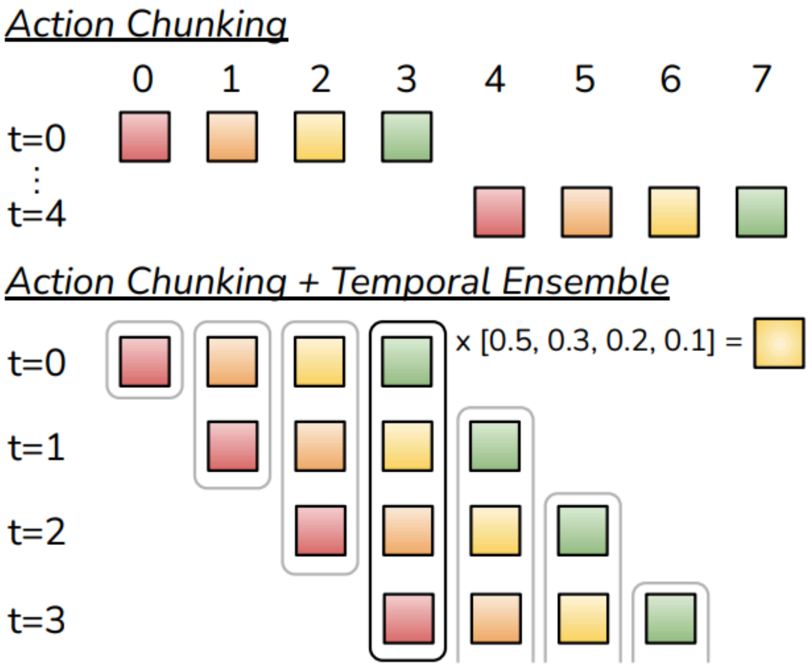


Fig. 5: We employ both Action Chunking and Temporal Ensembling when applying actions, instead of interleaving observing and executing.

Temporal Ensemble

- Creates **overlapping action chunks**

Temporal Ensemble

- Creates **overlapping action chunks**
- Queries the policy at **every step** for precise and smoother motions

Temporal Ensemble

- Creates **overlapping action chunks**
- Queries the policy at **every step** for precise and smoother motions
- **Combines** predictions using a weighted average

Temporal Ensemble

- Creates **overlapping action chunks**
- Queries the policy at **every step** for precise and smoother motions
- **Combines** predictions using a weighted average
- No additional training cost, only extra inference-time computation

Temporal Ensemble

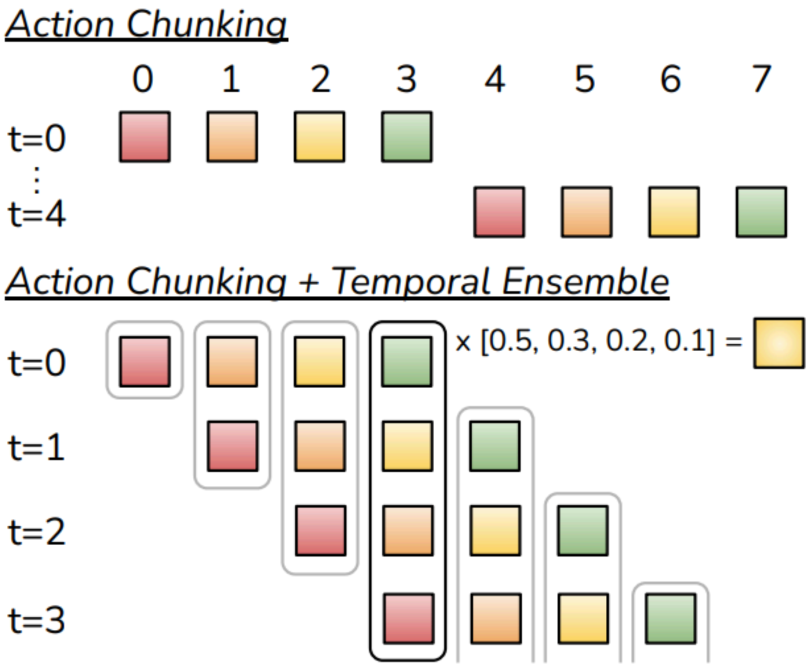


Fig. 5: We employ both Action Chunking and Temporal Ensembling when applying actions, instead of interleaving observing and executing.

Modeling Human Data

- Human demonstrations are **noisy and inconsistent**

Modeling Human Data

- Human demonstrations are **noisy and inconsistent**

- **Different** trajectories can be used for the same observation

Modeling Human Data

- Human demonstrations are **noisy and inconsistent**
- **Different** trajectories can be used for the same observation
- Human actions are more **stochastic** where precision matters less

Modeling Human Data

- Human demonstrations are **noisy and inconsistent**
- **Different** trajectories can be used for the same observation
- Human actions are more **stochastic** where precision matters less
- Policy must **focus on high precision** areas

Conditional Variational Autoencoder (CVAE)

- Train action chunking policy as a generative model

Conditional Variational Autoencoder (CVAE)

- Train action chunking policy as a generative model

- Only decoder (policy) used in deployment

Conditional Variational Autoencoder (CVAE)

- Train action chunking policy as a generative model
- Only decoder (policy) used in deployment
- Maximize log-likelihood of demonstration action chunks

Architecture

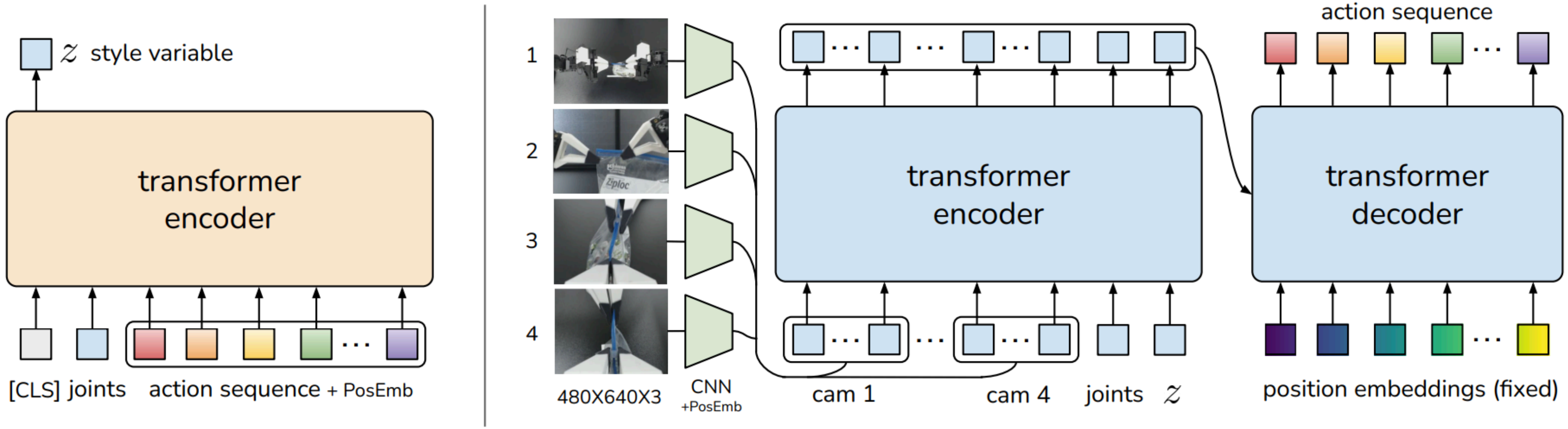


Fig. 4: *Architecture of Action Chunking with Transformers (ACT).* We train ACT as a Conditional VAE (CVAE), which has an encoder and a decoder. *Left:* The encoder of the CVAE compresses action sequence and joint observation into z, the style variable. The encoder is discarded at test time. *Right:* The decoder or policy of ACT synthesizes images from multiple viewpoints, joint positions, and z with a transformer encoder, and predicts a sequence of actions with a transformer decoder. z is simply set to the mean of the prior (i.e. zero) at test time.

Implementation of ACT: Encoder

- CVAE encoder and decoder implemented with **transformers**

Implementation of ACT: Encoder

- CVAE encoder and decoder implemented with **transformers**

- **BERT-like transformer** encoder used

Implementation of ACT: Encoder

- CVAE encoder and decoder implemented with **transformers**
- **BERT-like transformer** encoder used
- Inputs: current joint positions and target action sequence

Implementation of ACT: Encoder

- CVAE encoder and decoder implemented with **transformers**
- **BERT-like transformer** encoder used
- Inputs: current joint positions and target action sequence
- Outputs: mean and variance of "style variable" z

Implementation of ACT: Encoder

- CVAE encoder and decoder implemented with **transformers**
- **BERT-like transformer** encoder used
- Inputs: current joint positions and target action sequence
- Outputs: mean and variance of “style variable” z
- Only used during training - z set to 0 during test

Implementation of ACT: Decoder

- Predicts next k actions
- Inputs: current observations and z
- Observations: 4 RGB images and joint positions of 2 robot arms
- ResNet18 used for image processing

Implementation of ACT: Decoder

- Transformer encoder synthesizes information
- Transformer decoder generates action sequence
- L1 loss used for precise action sequence modeling

Experiment Tasks

- Slide Ziploc: Grasp and open ziploc bag slider
- Slot Battery: Insert battery into remote controller slot
- Open Cup: Open lid of small condiment cup
- Thread Velcro: Insert velcro cable tie into loop
- Prep Tape: Cut and hang tape on box edge
- Put On Shoe: Put shoe on mannequin foot and secure velcro strap
- Transfer Cube (sim): Transfer red cube to other arm
- Bimanual Insertion (sim): Insert peg into socket in mid-air

Challenges

- Requires fine-grained bimanual control

Challenges

- Requires fine-grained bimanual control
- Perception challenges (e.g., transparency, low contrast)

Challenges

- Requires fine-grained bimanual control
- Perception challenges (e.g., transparency, low contrast)
- Random initial placement of objects

Challenges

- Requires fine-grained bimanual control
- Perception challenges (e.g., transparency, low contrast)
- Random initial placement of objects
- Need for visual feedback to correct perturbations

Challenges

- Requires fine-grained bimanual control
- Perception challenges (e.g., transparency, low contrast)
- Random initial placement of objects
- Need for visual feedback to correct perturbations
- Precise manipulation needed

Data Collection

- Collected using ALOHA teleoperation for 6 real-world tasks

Data Collection

- Collected using ALOHA teleoperation for 6 real-world tasks
- Each episode: 8-14 seconds (400-700 time steps at 50Hz)

Data Collection

- Collected using ALOHA teleoperation for 6 real-world tasks
- Each episode: 8-14 seconds (400-700 time steps at 50Hz)
- 50 demonstrations per task (100 for Thread Velcro)

Data Collection

- Collected using ALOHA teleoperation for 6 real-world tasks
- Each episode: 8-14 seconds (400-700 time steps at 50Hz)
- 50 demonstrations per task (100 for Thread Velcro)
- Total: 10-20 minutes of data per task

Data Collection

- Collected using ALOHA teleoperation for 6 real-world tasks
- Each episode: 8-14 seconds (400-700 time steps at 50Hz)
- 50 demonstrations per task (100 for Thread Velcro)
- Total: 10-20 minutes of data per task
- Scripted policy / human demonstrations for simulated tasks

Human demonstrations are stochastic

- Mid-air handover example: position varies each time

Human demonstrations are stochastic

- Mid-air handover example: position varies each time
- Policy must learn dynamic adjustments, not memorization

Experiment Comparison

- Compared ACT with four methods:
  - BC-ConvMLP: Simple baseline with convolutional network
  - BeT: Uses Transformers, no action chunking, separate visual encoder
  - RT-1: Transformer-based, predicts one action from history
  - VINN: Non-parametric, uses k-nearest neighbors

Experiment Comparison

- Compared ACT with four methods:
  - BC-ConvMLP: Simple baseline with convolutional network
  - BeT: Uses Transformers, no action chunking, separate visual encoder
  - RT-1: Transformer-based, predicts one action from history
  - VINN: Non-parametric, uses k-nearest neighbors

- ACT directly predicts continuous actions

Experiment Results

Experiment Results

- ACT outperforms all prior methods in both simulated and real tasks

Experiment Results

- ACT outperforms all prior methods in both simulated and real tasks

- Simulated tasks: ACT shows 20%-59% higher success rates

Experiment Results

- ACT outperforms all prior methods in both simulated and real tasks
- Simulated tasks: ACT shows 20%-59% higher success rates
- Real-world tasks: Slide Ziploc (88%), Slot Battery (96%)

Experiment Results

- ACT outperforms all prior methods in both simulated and real tasks
- Simulated tasks: ACT shows 20%-59% higher success rates
- Real-world tasks: Slide Ziploc (88%), Slot Battery (96%)
- ACT’s performance in Thread Velcro was lower (20%) due to precision challenges

Ablation: Action Chunking and Temporal Ensembling

- Action chunking reduces compounding errors by dividing sequences into chunks
- Performance improves with increasing chunk size, best at k = 100
- Temporal ensembling further improves performance by averaging predictions

Ablation: Training with CVAE

- CVAE models noisy human demonstrations
- Essential for learning from human data, removing CVAE objective significantly drops performance

Ablation: Training with CVAE

- CVAE models noisy human demonstrations
- Essential for learning from human data, removing CVAE objective significantly drops performance
- Human data success rate drops from 35.3% to 2% without CVAE

Ablation: Is High-Frequency Necessary?

- Human shows higher performance at 50Hz compared to 5Hz

Ablation: Is High-Frequency Necessary?

- Human shows higher performance at 50Hz compared to 5Hz

- Tasks: threading zip cable tie and unstacking plastic cups

Ablation: Is High-Frequency Necessary?

- Human shows higher performance at 50Hz compared to 5Hz
- Tasks: threading zip cable tie and unstacking plastic cups
- 50Hz: faster and more accurate task completion

Ablation: Is High-Frequency Necessary?

- Human shows higher performance at 50Hz compared to 5Hz
- Tasks: threading zip cable tie and unstacking plastic cups
- 50Hz: faster and more accurate task completion
- 50Hz reduces teleoperation time by 62% compared to 5Hz

Ablation graphs

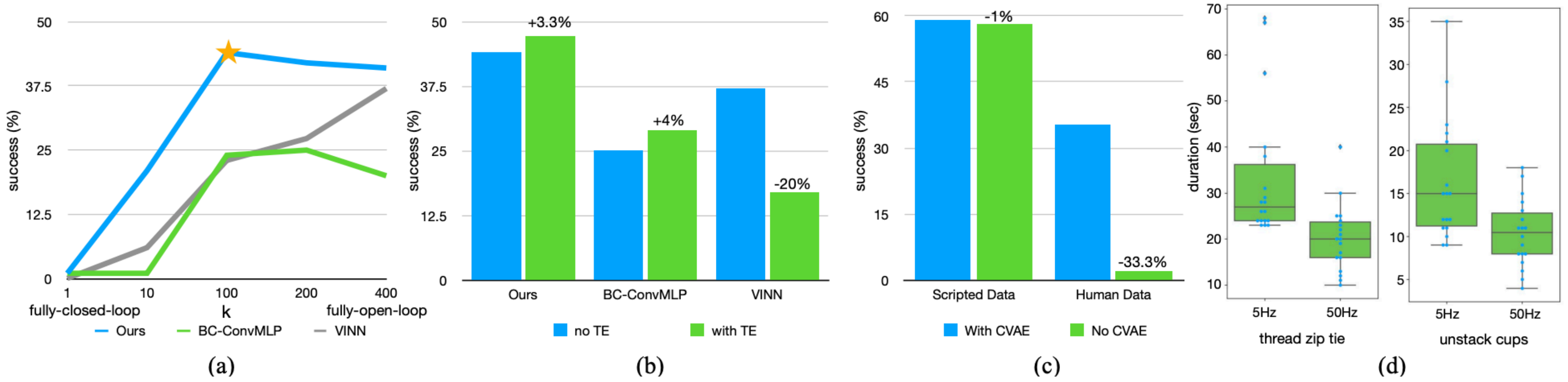


Fig. 8: *(a)* We augment two baselines with action chunking, with different values of chunk size k on the x-axis, and success rate on the y-axis. Both methods significantly benefit from action chunking, suggesting that it is a generally useful technique. *(b)* Temporal Ensemble (TE) improves our method and *BC-ConvMLP*, while hurting *VINN*. *(c)* We compare with and without the CVAE training, showing that it is crucial when learning from human data. *(d)* We plot the distribution of task completion time in our user study, where we task participants to perform two tasks, at 5Hz or 50Hz teleoperation frequency. Lowering the frequency results in a 62% slowdown in completion time.

Limitations and Conclusion

- Presented a low-cost system for fine manipulation
- Components: ALOHA teleoperation system and ACT imitation learning algorithm
- Enables learning fine manipulation skills in real-world
- Examples: Opening a translucent condiment cup, slotting a battery (80-90% success rate, 10 min demonstrations)

- Limitations: Tasks beyond current capabilities, e.g., buttoning a dress shirt
- Hope: Important step and accessible resource for advancing fine-grained robotic manipulation