Learning Fine-Grained Bimanual Manipulation with Low-Cost Hardware

RSS 2023

양현서

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About

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Motivation

- **Fine manipulation tasks** such as
  - threading cable ties
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  - 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

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- 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

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- User-friendly

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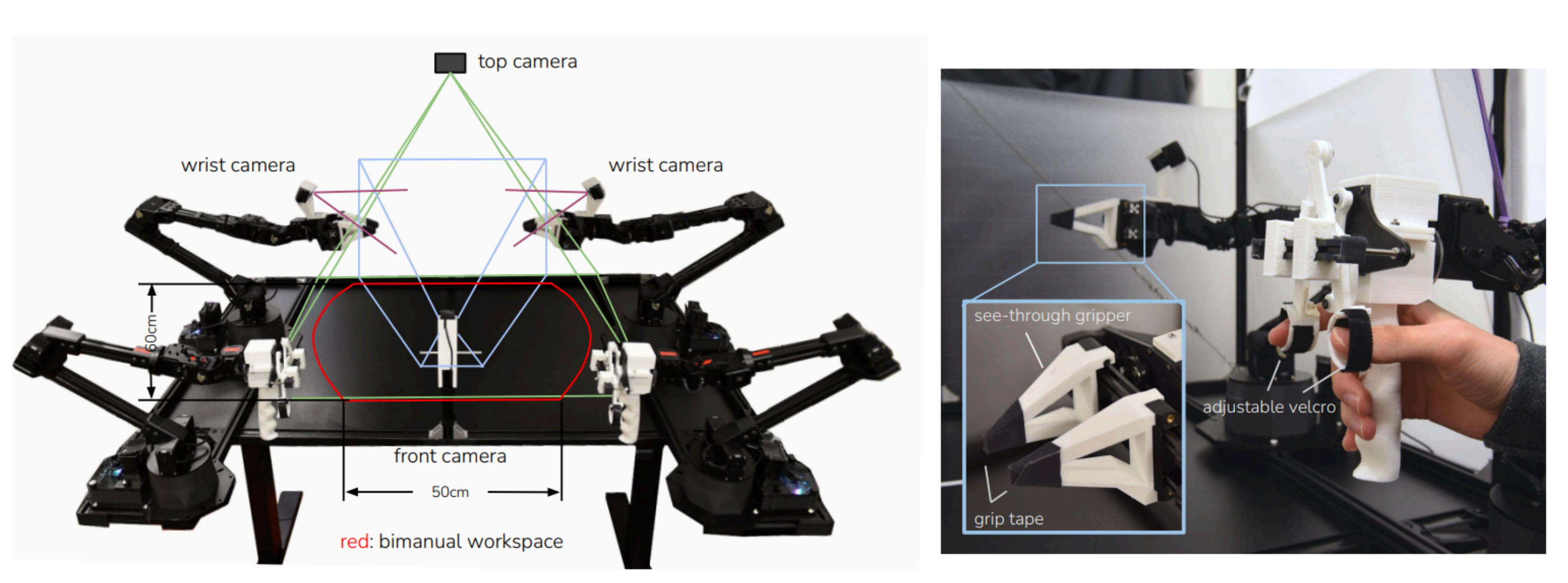
- Easy-to-build

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



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  - Compounding errors in policy
  - Non-stationary human demonstrations

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- **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

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- **Challenge: Compounding errors**

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

- Mitigates issues with non-stationary demonstrations

Action Chunking

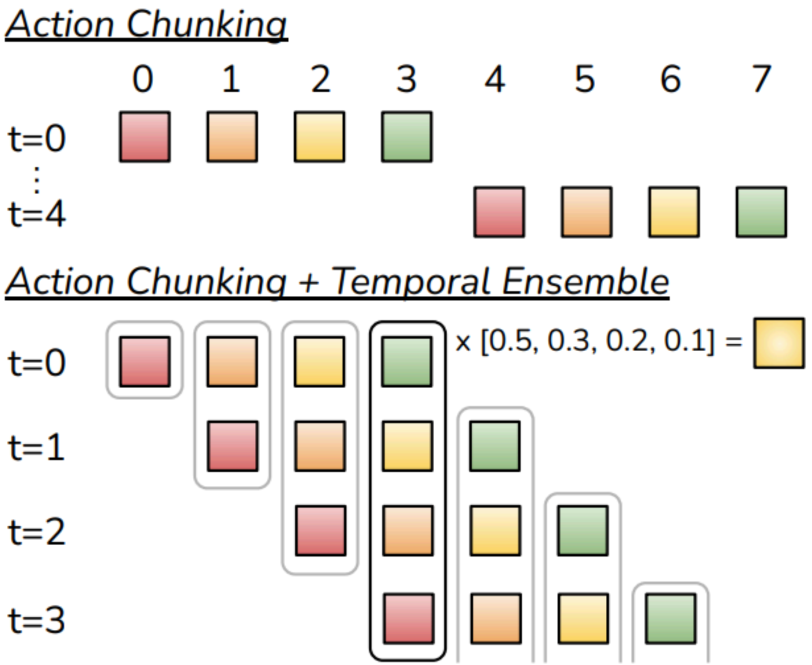

Fig. 5: We employ both Action Chunking and Temporal Ensembling when applying actions, instead of interleaving observing and executing.

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- No additional training cost, only extra inference-time computation

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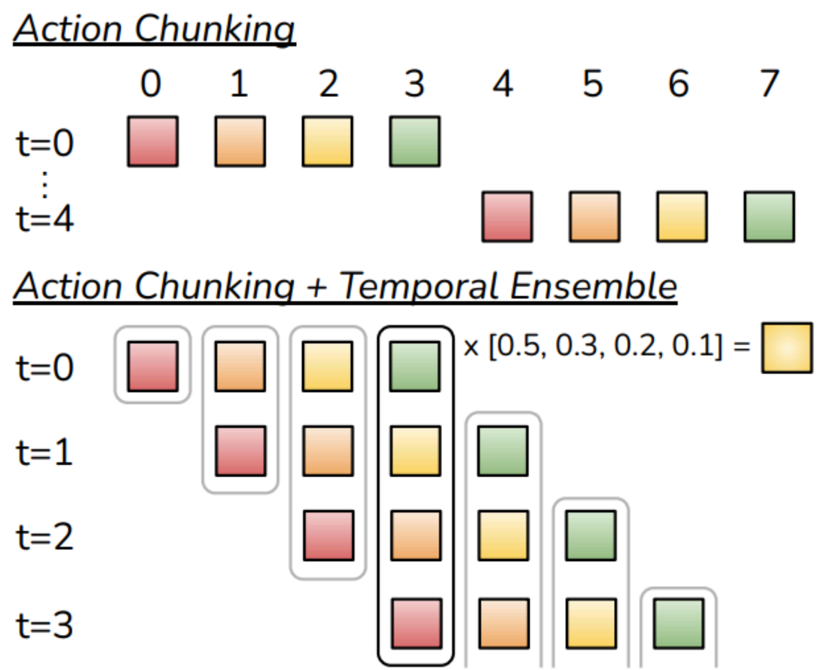

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- **Different** trajectories can be used for the same observation
- Human actions are more **stochastic** where precision matters less
- Policy must **focus on high precision** areas

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- Maximize log-likelihood of demonstration action chunks

Architecture

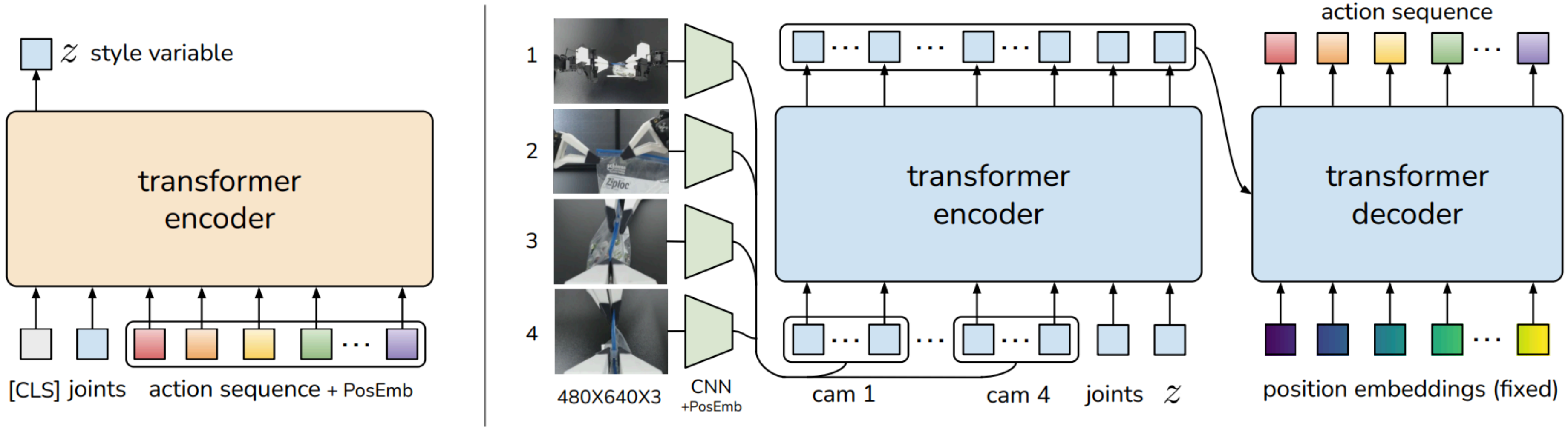

Fig. 4: *Architecture of Action Chunking with Transformers (ACT).* We train ACT as a Conditional VAE (CVAE), which has an encoder and a decoder. *Left:* The encoder of the CVAE compresses action sequence and joint observation into z, the style variable. The encoder is discarded at test time. *Right:* 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.

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- 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

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- Perception challenges (e.g., transparency, low contrast)
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- Need for visual feedback to correct perturbations
- Precise manipulation needed

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- 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
  - 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

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- ACT directly predicts continuous actions

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- 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

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

- Human data success rate drops from 35.3% to 2% without CVAE

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- 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

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