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CS4320TU Applied AI Project

Imitation Learning for Skill Transfer in Human-Robot Teleoperation

Group Member:
Marco Schouten (5352908)
Chenghao Xu (5266068)

Supervisor:
R Venkatesha Prasad
Vineet Gokhale
Ashutosh Simha

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Project Background

With the rapid development of 5G technology, teleoperation could perform remote control to operate the robot at a remote distance. Meanwhile, Users expect that the robot can perform similar actions as precisely as human.

Applications:
Service Robot; Biped Robot; Surgery Robot;

Main Problem:

- Transmission time delay
- Transmission data size

Fig 1. the Surgery Performed by Da Vinci Robot

Fig 2. Imitation Learning for Human-robot Interaction

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Project Goal

As for the various human action, develop an AI model to learn the specific trajectories of human arm, then regenerate the similar trajectories by robot using minimal representation inputs.

- Kinect Camera records human actions
- Model the input angle data encoder in joint space
- Model the robot trajectory decoder in cartesian space
- Develop the trajectory comparison metric

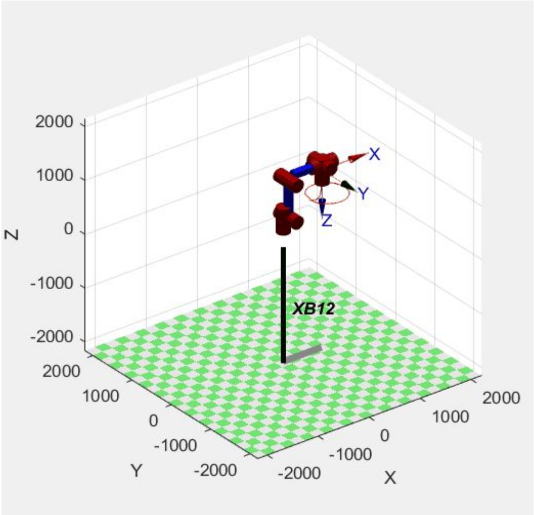

Fig 3. example for 6-axis Industrial Robot

Control interval: 1 ms = 0.001 s
Number of control input: 6

Reproduce the trajectory in the past 1 s:
6000 float number data
\+ force data & torque data

Approach Design

Solution is a two-fold

- (A) implementing a smart encoding to represent the task trajectory with a small set of parameters
- (B) building a model able to generate a trajectory given an input task trajectory

Trajectory encoding: GMM-GMR

1) *Calinon et al. 2015* approached skill encoding as a clustering problem. Instead of modeling the regression function directly, they estimate a joint-distribution over the state variables, and perform regression through conditioning.

2) During reproduction, the motion is retrieved through statistical inference using Gaussian Mixture Regression (GMR).

The linear transformation properties of the Gaussian Mixture Model (GMM) allow the modeling of primitives in different coordinate systems.

By relating coordinate systems to the task context (e.g. objects or landmarks), a context-adaptive version of GMM-GMR, named Task-Parameterized GaussianMixtureModel (TP-GMM), is realized.

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Task Parametrization

achieves strong context adaptation by representing task motion in local coordinate systems. It observes demonstrations from **different perspectives.**

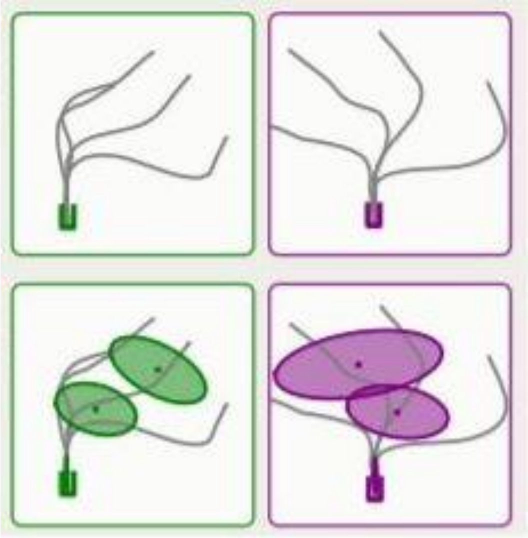
Requires three elements:

1) a context parameterization which defines the relation between local (context-independent) coordinate systems, and a global coordinate system;
2) a model parameterization to compactly represent the local movement representations;
3) merging method that allows to fuse the contextualized movement representation

Conceptual Description (1)

Projected data X to a latent space Z is encoded using Gaussian Mixture Model (GMM), which approximates the joint Probability density function

P(X, t)



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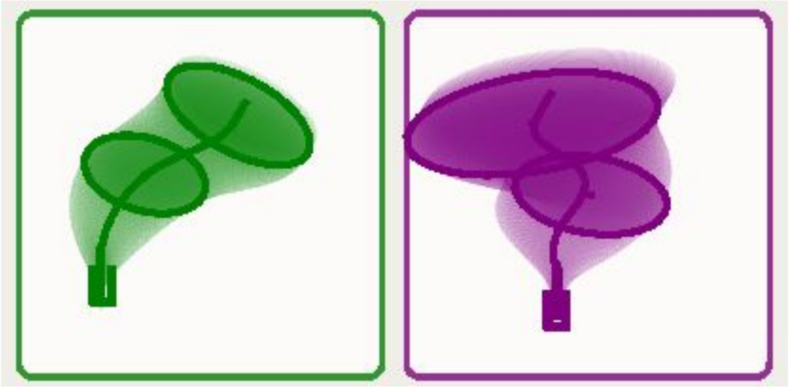
Conceptual Description (2)

Compute, with GMR, a tube of Gaussians for each reference frame

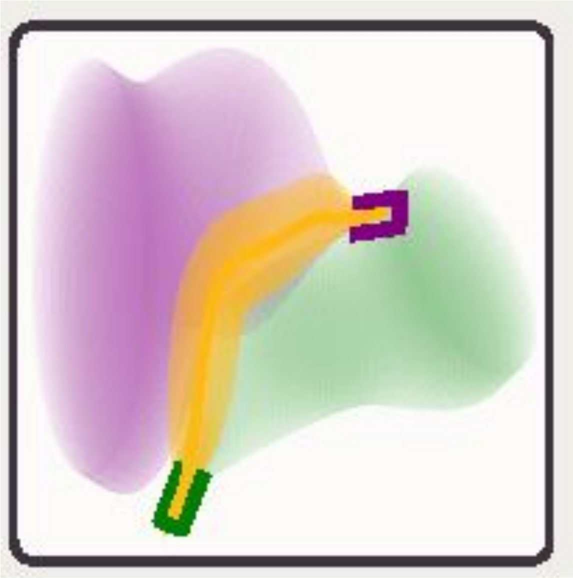
P(X | t)



Conceptual Description (3)

Given new input, the model can retrieve the most likely trajectory.

(first by projecting the reference frames to the global frame, than computing the product of Gaussians to retrieve the trajectory



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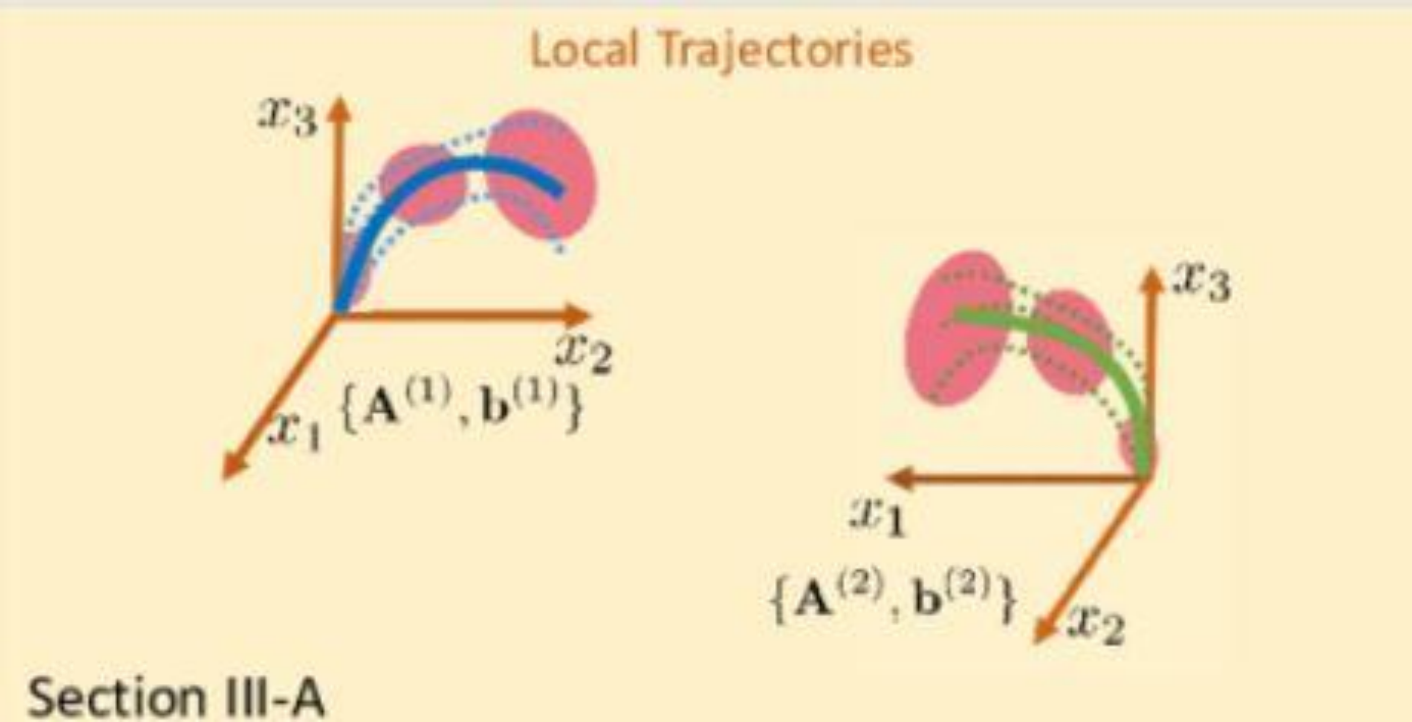
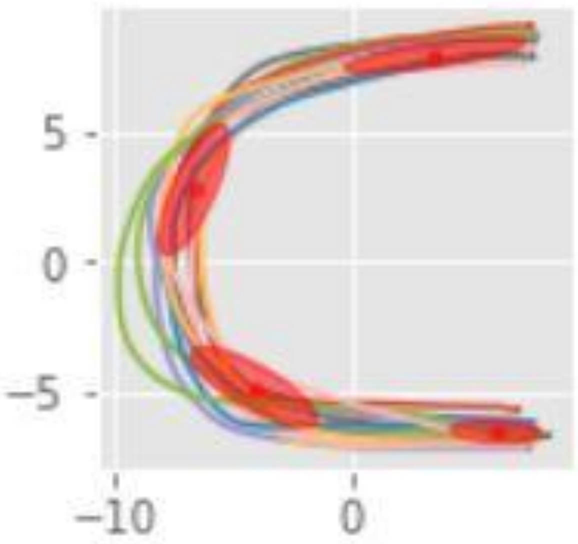
Approach Design summary



Current Progress

- The GMM model
- Expectation Maximization algorithm
- tested on a 2D latent space



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Future Plan

Solution is a two-fold

- (A) implementing a *smart* encoding to represent the task trajectory with a small set of parameters **(investigating with PCA, MDS, ISOMAP, Geometry)**
- (B) building a model able to generate a trajectory given an input task trajectory **(adding GMR)**

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Week 3	1. Install the coppeliaSim platform √ 2. Search for relevant literature √ 3. Write down the goal of the project √
Week 4	1. Complete searching for literature √ 2. AI concept design for the project √ 3. Pick up Kinect, learn how Kinect works √
Week 5	1. Initiate decision for AI model √ 2. Start learning how to collect data √ 3. Pick up the initial kinematic data √
Week 6	1. Accomplish dimension reduction and Gaussian model, and plot the data in the feature space √ 2. Prepare for the mid-term presentation √ 3. Generate fake data of human arm action √
Week 7	1. Learn GMR for the reproduction and segmentation 2. Accomplish the GMR coding part to regenerate trajectory 3. Realize the Kinect human action record and angle reflection
Week 8	1. Improve the model design and tune hyperparameters 2. Work on performance evaluation and establish of action library
Week 9	1. Summary and evaluate the result 2. Finish the project report

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