A novel robotic handwriting-learning system based on Dynamic Movement Primitives (DMP)

Reporter: Jing Wu, Qian Luo

1, Project description

2, DMP introduction

3, Modification

4, Experiment environment

5, Experiment results

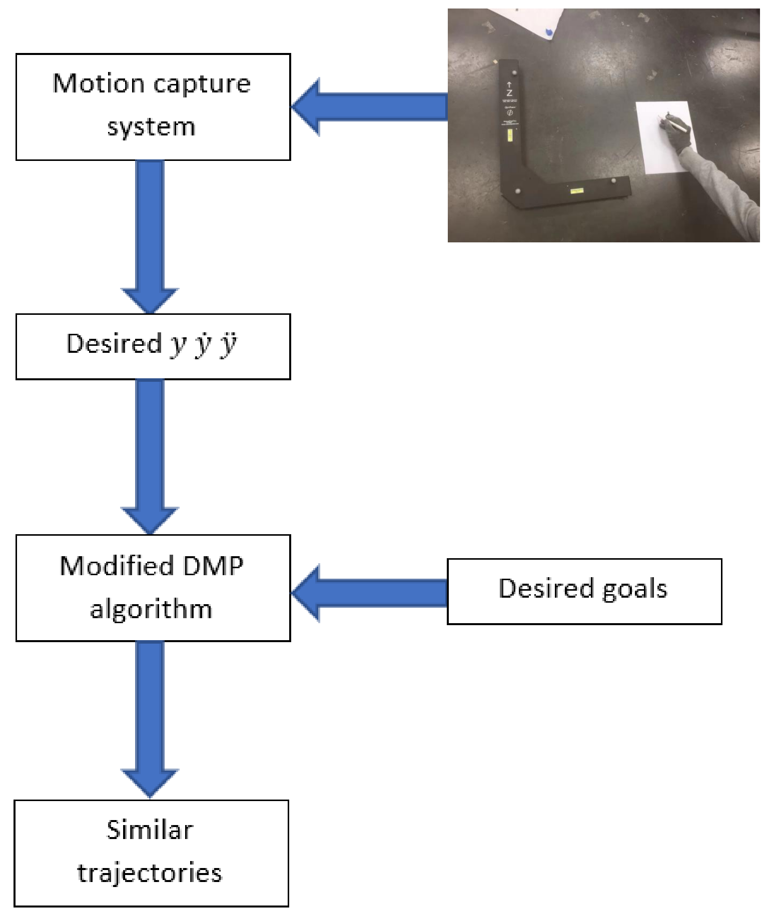
6, Future work

1, Project description

- **Goal:** Design a robot learning system which could capture human's handwriting trajectories(demonstration) and learn from them to create its own handwriting trajectories.
- **Two stages:** Firstly, the robot will precisely imitate human's certain handwriting trajectory. Secondly, the robot will learn the "style" of human's handwriting trajectory and create its own stylistic trajectory based on a standard one.
- **What we have achieved:** We have successfully accomplished the goal in the first stage with our modified DMP algorithm. In this project update, we will analyze our learned trajectories to show the efficiency of our modified DMP algorithm.

1, Project description

- In the first place, we used motion capture hardware system to collect human handwriting data. Then we input the data to our modified DMP algorithm to generate a set of learned points, which are similar to the original ones.



2, DMP Introduction

- Dynamic Movement Primitives (DMP) are a generic framework for motor representation based on nonlinear dynamic systems
- The core idea behind DMP is to perterb a simple linear dynamical system(the left part of equation(1)) with a non-linear component(f) to acquire smooth movements of arbitrary shape.

DMP equations

$$\tau \ddot{y} = \alpha_z(\beta_z(g - y) - \tau \dot{y}) + f \quad (1)$$

$$\tau \dot{x} = -\alpha_x x \quad (2)$$

$$f = \frac{\sum_{i=1}^{N} \psi_i w_i}{\sum_{i=1}^{N} \psi_i} x \quad (3)$$

$$\psi_i = \exp(-h_i(x - c_i)^2) \quad (4)$$

2, DMP Introduction

- To determine the weights of each kernel, we employ Locally Weighted Regression(LWR) to minimize the mean square error(MSE)

$$MSE = \frac{1}{T}\sum_{j=1}^{T}(y_d - y_{learned})^2)$$

- Thus, by using LWR, we can get optimal weights value:

$$w_i = \frac{s^T\psi_i \mathrm{f}}{s^T\psi_i s}$$

$$s = \begin{bmatrix} x_{t_o}(y_g - y_o) \\ \vdots \\ x_{t_N}(y_g - y_o) \end{bmatrix}, \psi_i = \begin{bmatrix} \psi_i(t_o) & \dots & 0 \\ 0 & \ddots & 0 \\ 0 & \dots & \psi_i(t_N) \end{bmatrix},$$

$$\mathrm{f} = \begin{bmatrix} \ddot{y}_{t_o} - \alpha_y(\beta_y(y_g - y_{t_o}) - \dot{y}_{t_o}) \\ \vdots \\ \ddot{y}_{t_N} - \alpha_y(\beta_y(y_g - y_{t_N}) - \dot{y}_{t_N}) \end{bmatrix}.$$

3, DMP Modification

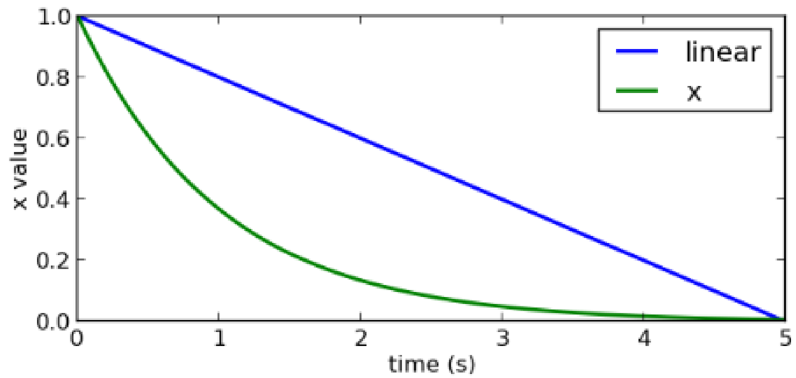
- Due to the complexity of demonstrated handwriting trajectories and the existence of noise, the imitation results were not satisfying by using original DMP algorithm. Thus, we modified the original algorithm to improve its stability and flexibility.

- There are two major modifications:
- The first is to replace the exponential decay system with a linear decay system
- The second is to use a truncated version of Gaussian Kernel Ψ_i

3, DMP Modification

linear decay system

$$\dot{x} = -\alpha_x x \quad \Rightarrow \quad \dot{x} = -1/T$$



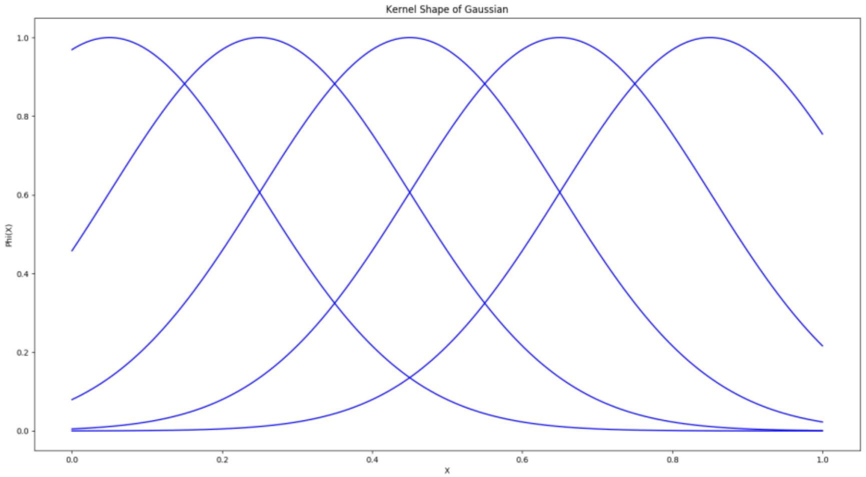
- The advantage of using linear decay system is: The desired magnitude of weights of terminal kernels(as x close to o) are significantly less. It means that, in linear dacay system, it is more possible to fit curves near the endpoint.

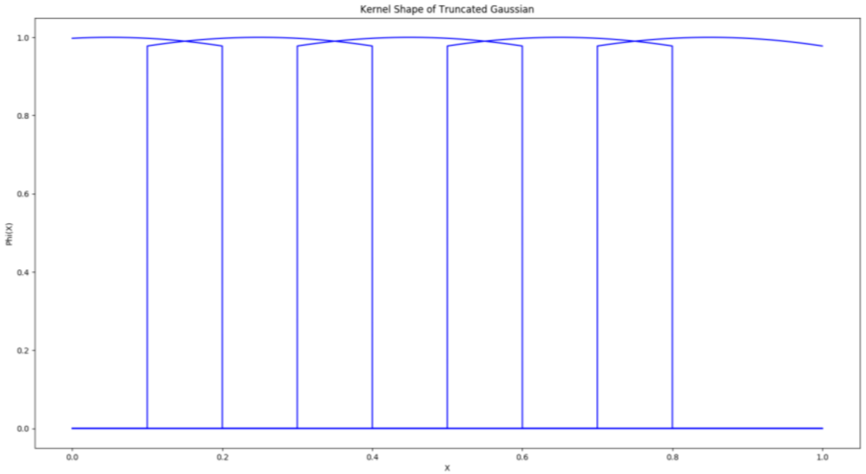
3, DMP Modification

truncated version of Gaussian Kernel Ψi

$$\Psi_i = \exp(-h_i(x - c_i)^2)$$

$$\Psi_i = \begin{cases} \exp(-\frac{h_i}{2}(x - c_i)^2), & \text{if } x - c_i \leq \theta_i \\ 0, & \text{otherwise} \end{cases}$$





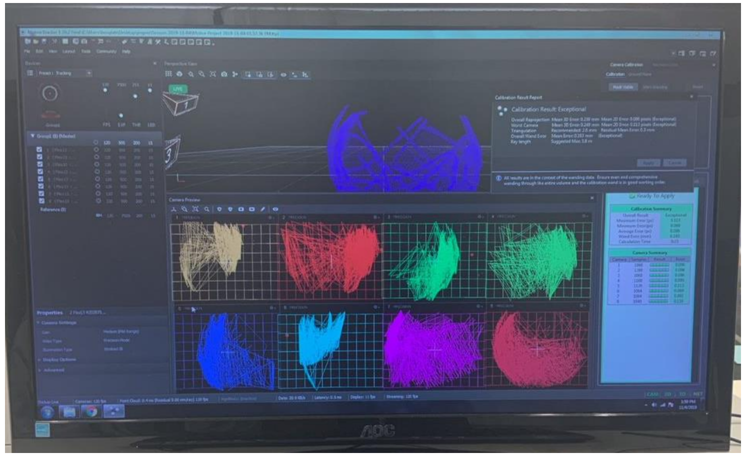
- The advantage of using truncated kernels is that it limits the number of kernels affected by trajectory modification. That's to say, every kernel works more independently, allowing the weights of each kernel more characteristic.

4, Experiment environment

Motion Capture Equipment

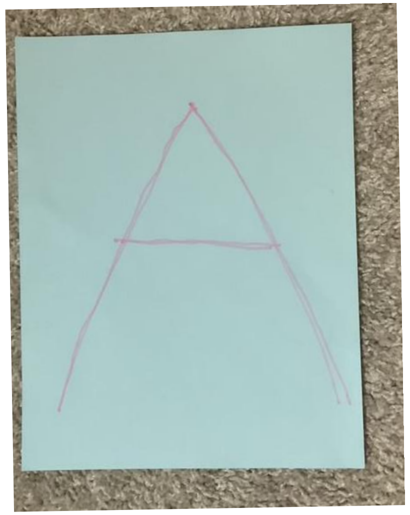
Rigid body as origin

4, Experiment environment



Calibration process (error at lease less than 0.1 cm)

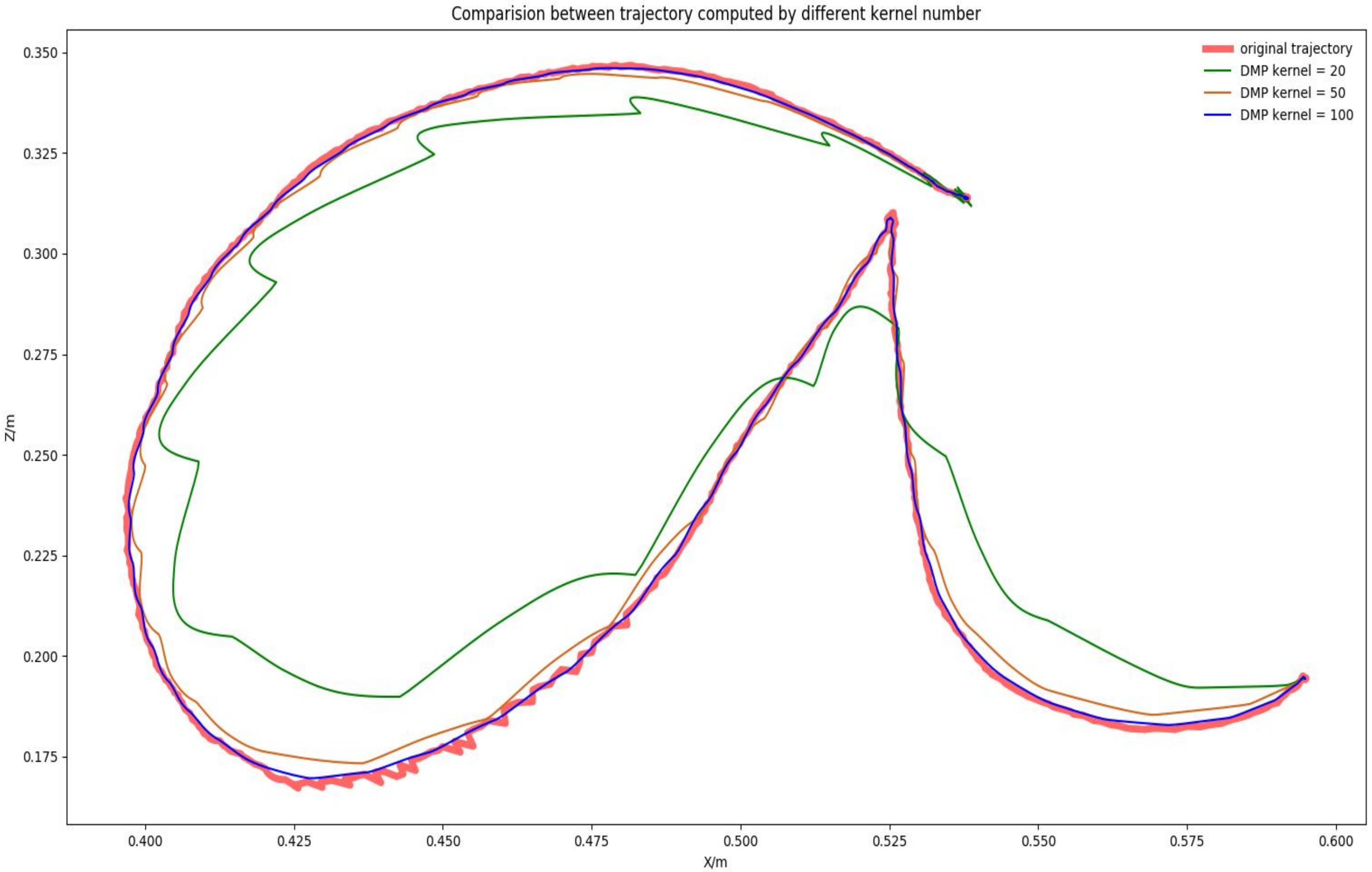
Motion Capture Equipment

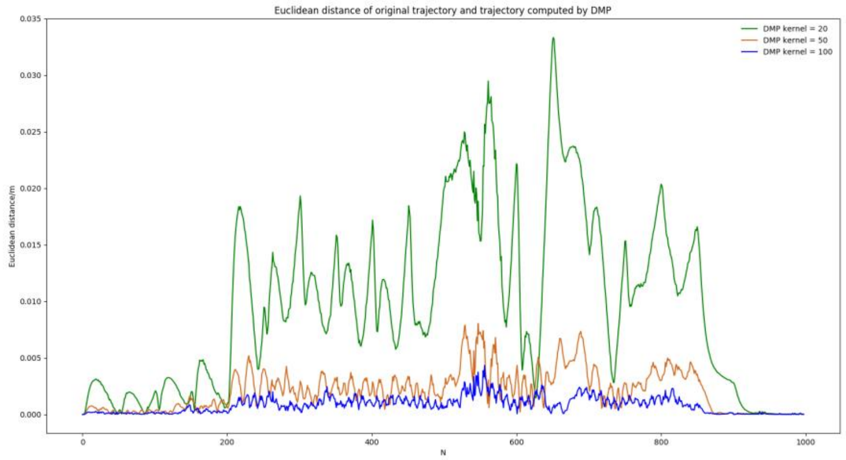


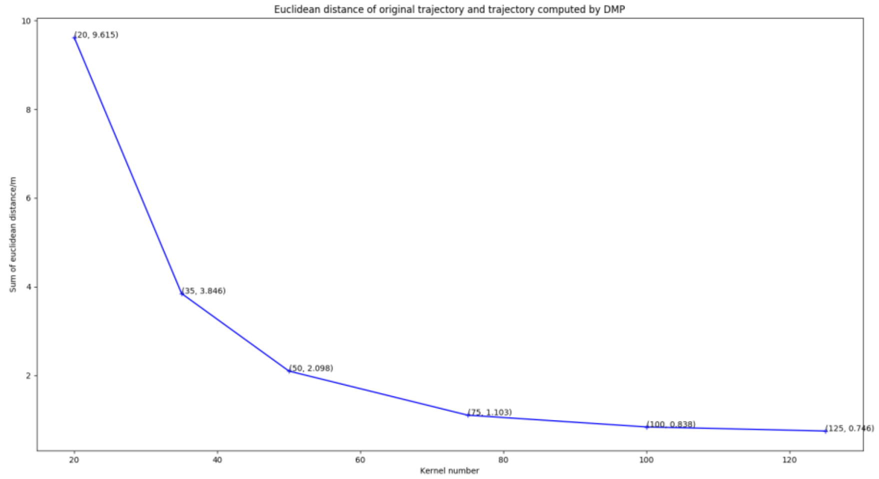
Written Letter on paper

5, Experiment results

Influence of the number of kernel number

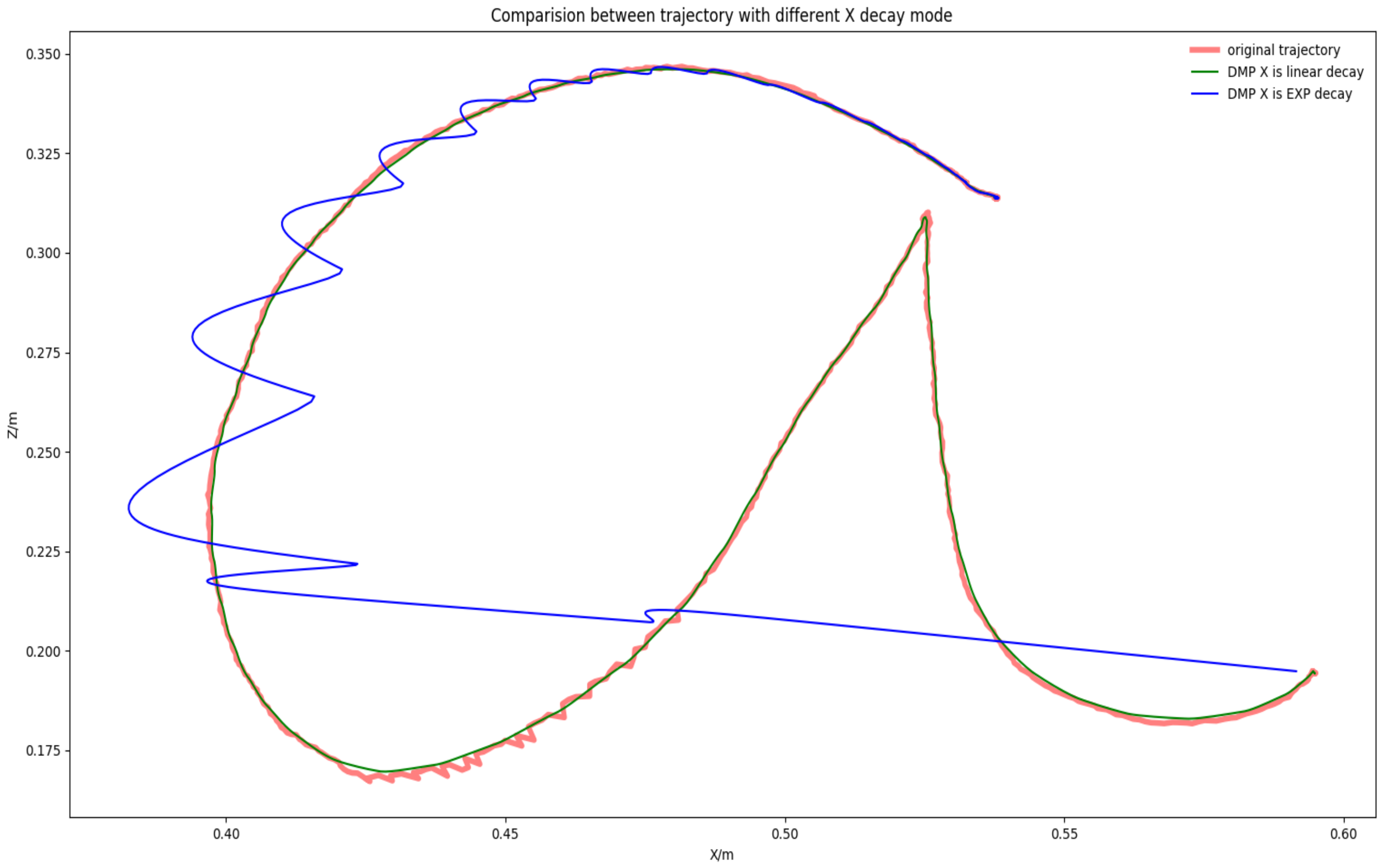


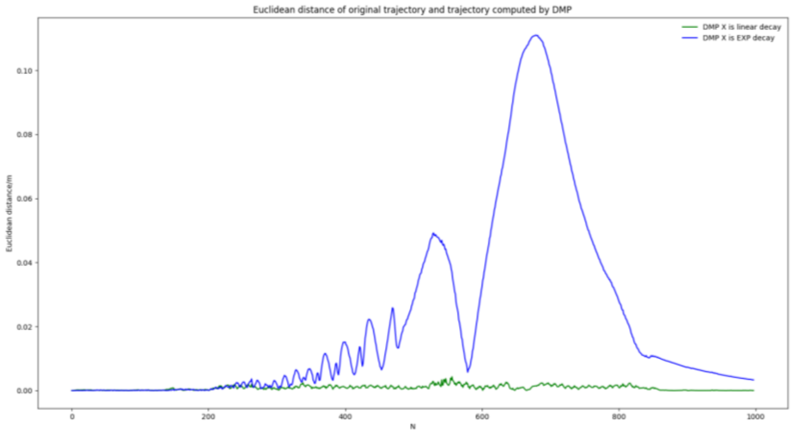




5, Experiment results

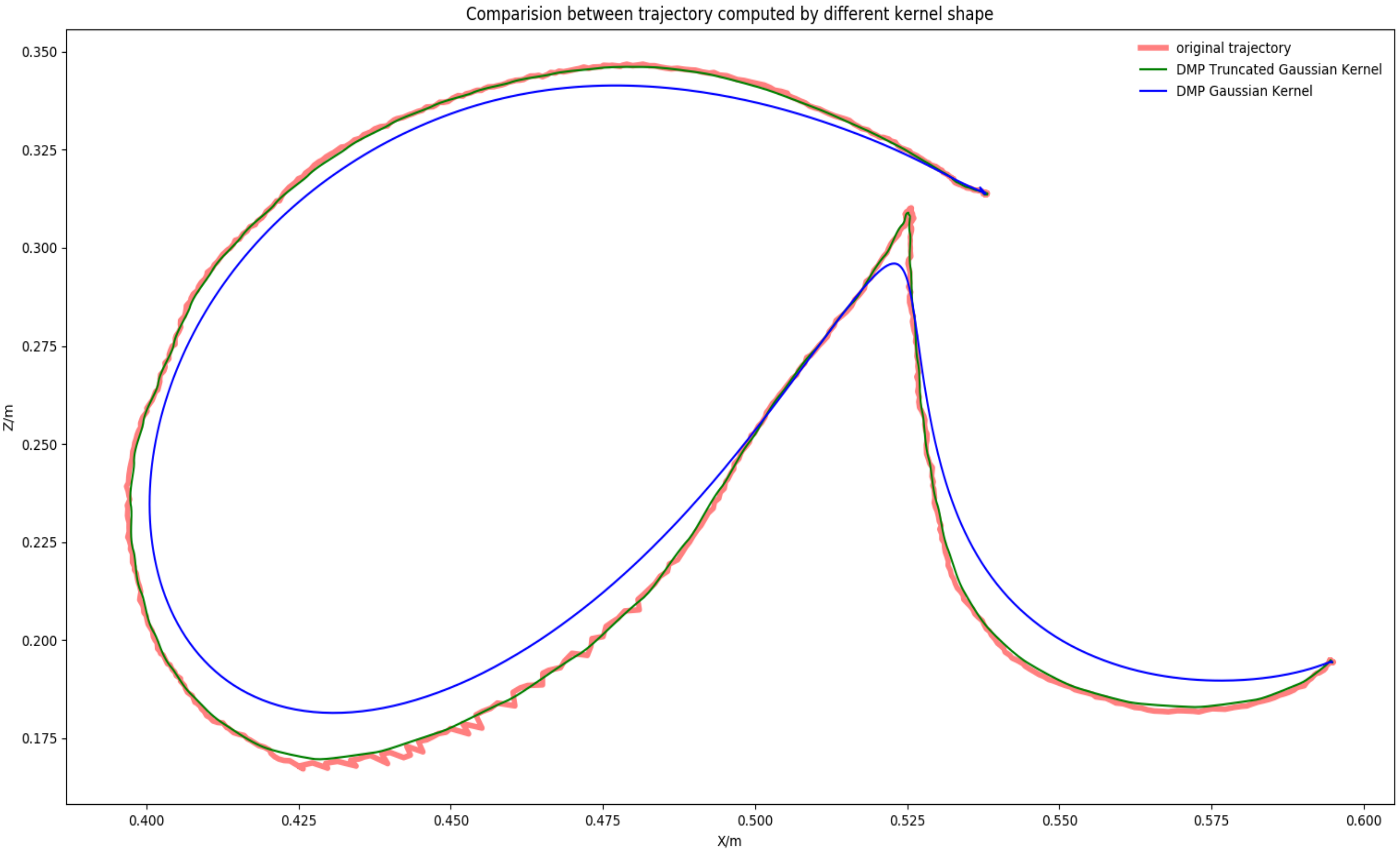
Influence of the number of x decay type

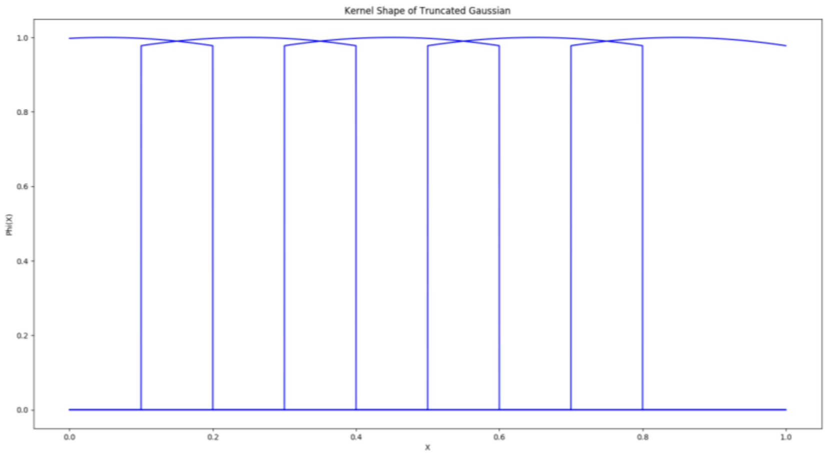


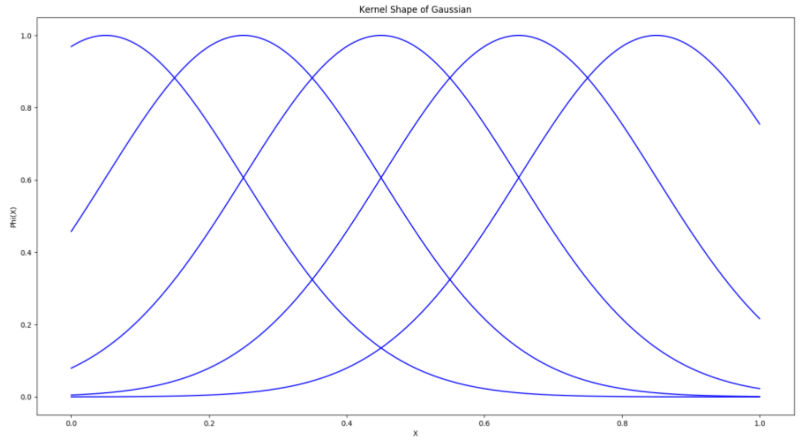


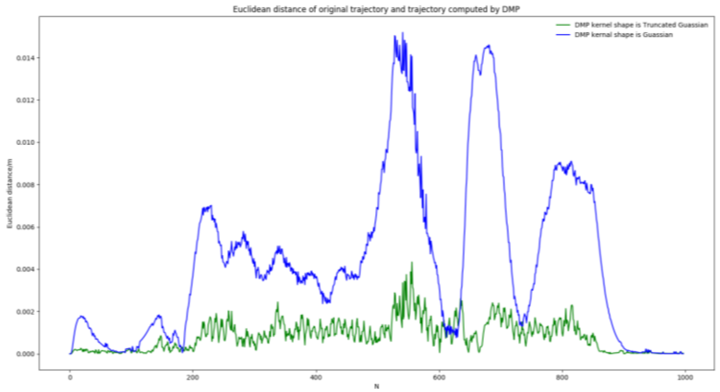
5, Experiment results

Influence of the kernel shape



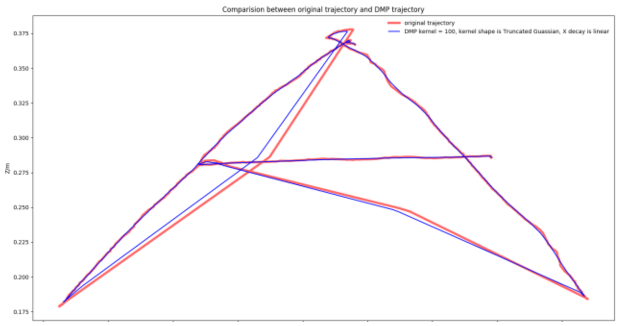


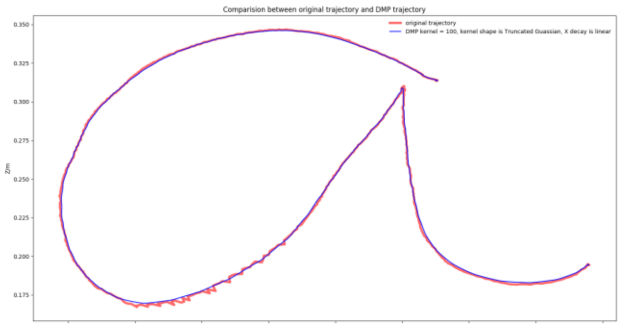


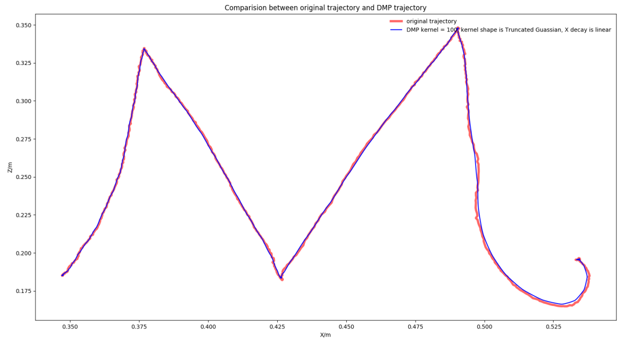


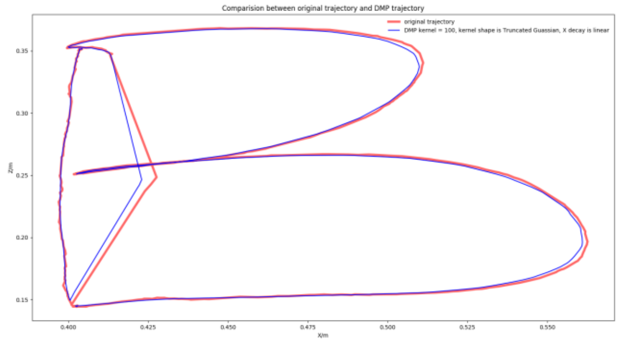
5, Experiment results

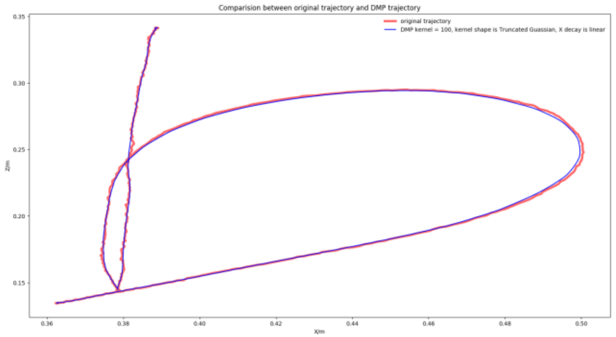
Results of some letter trajectories

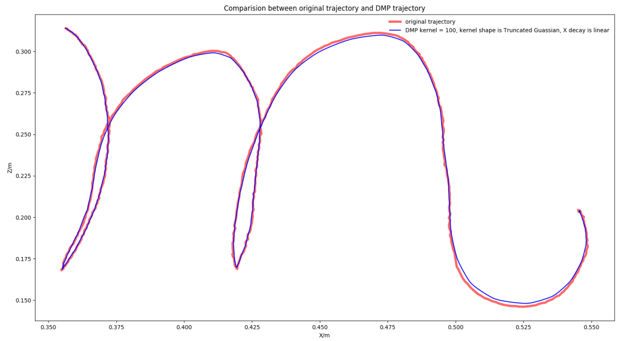


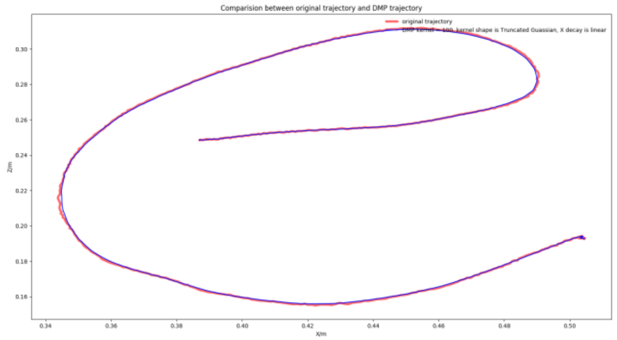


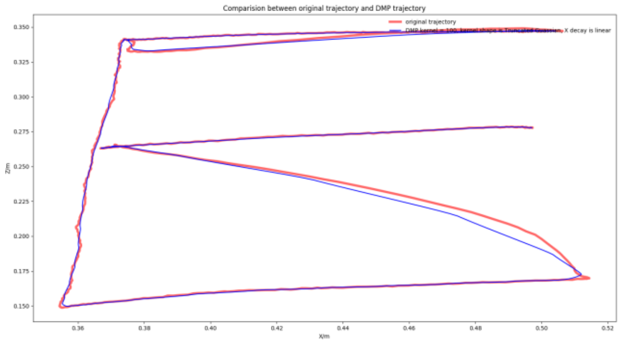




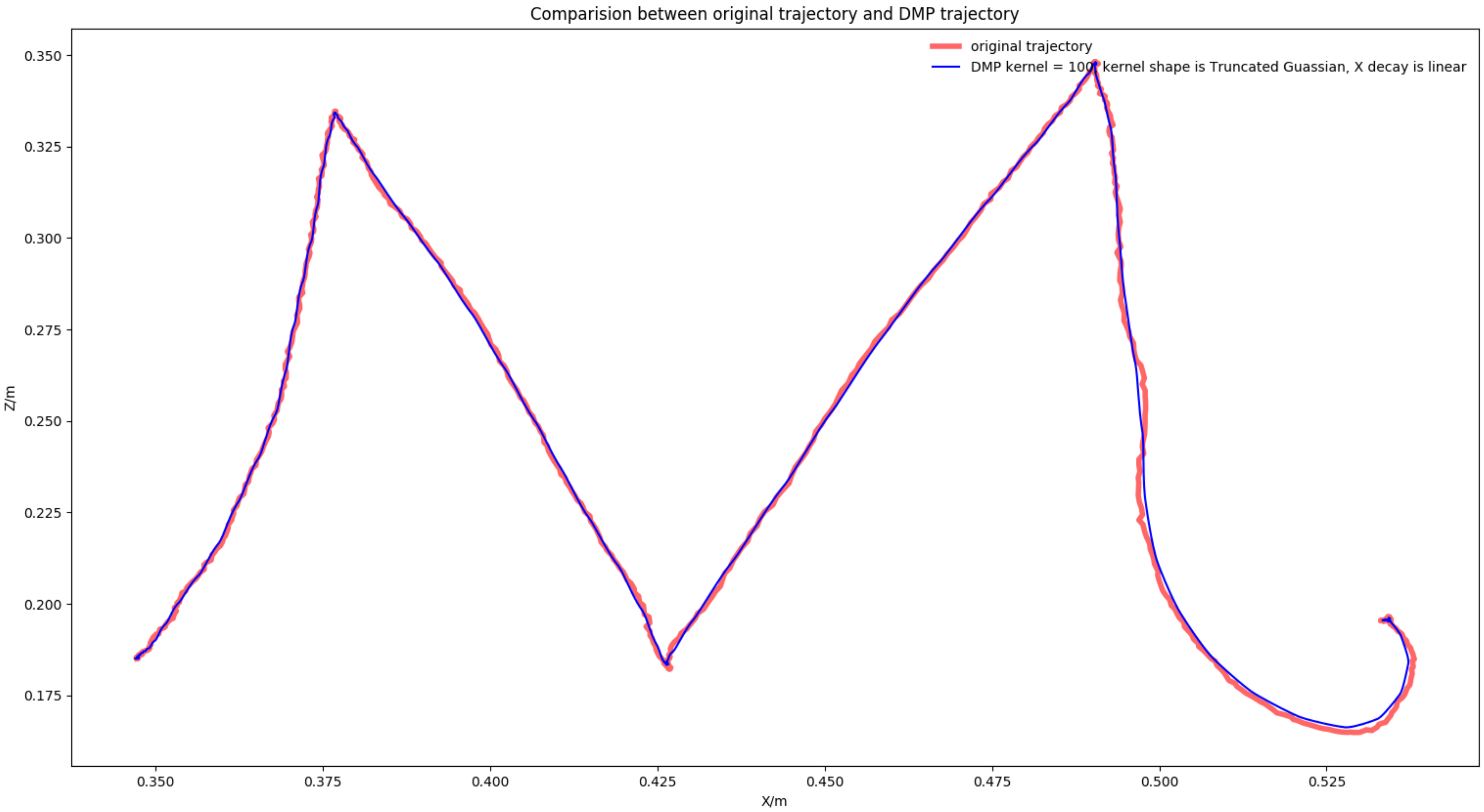




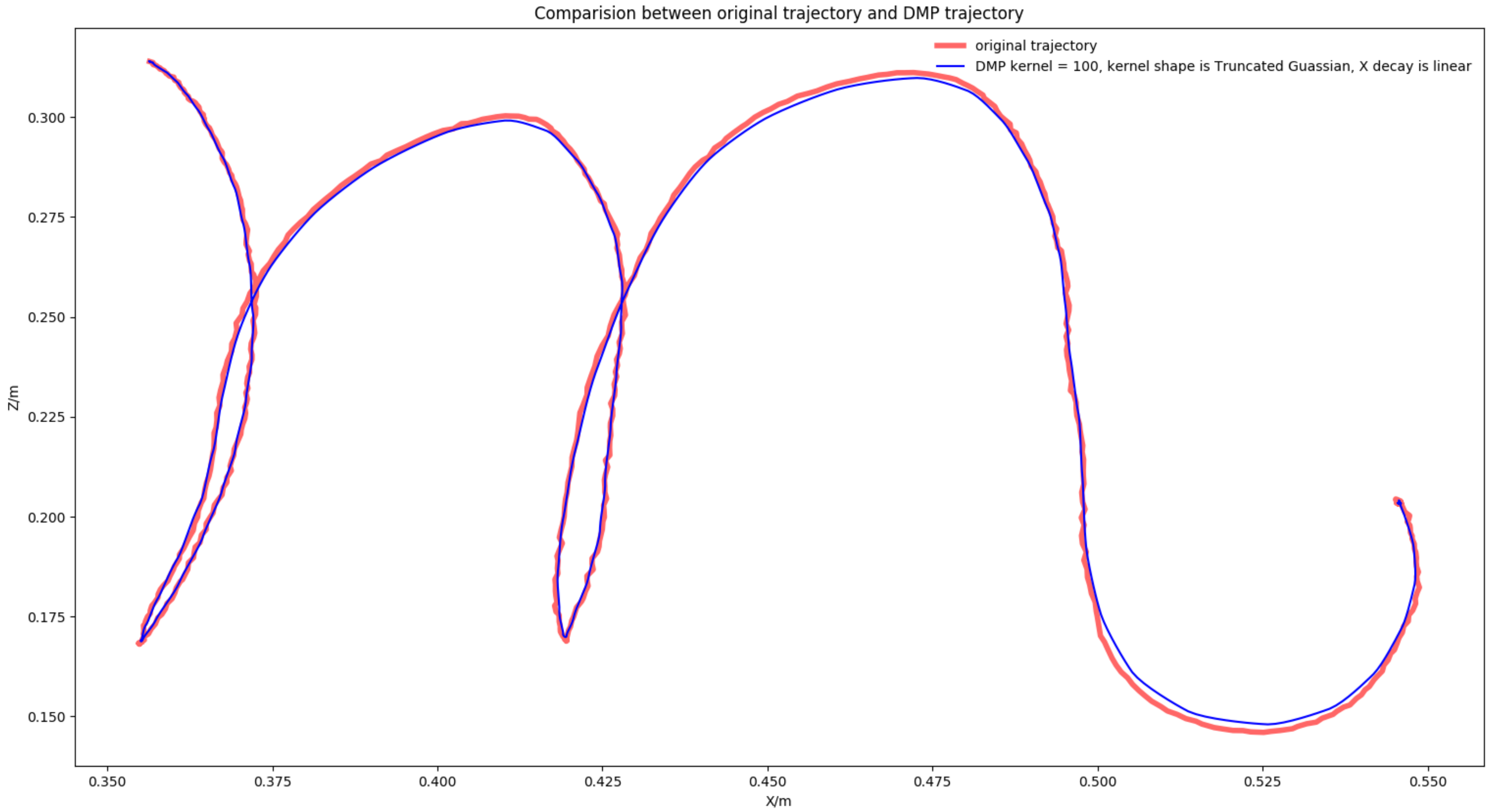




5, Experiment results



5, Experiment results



6, Future work

- invite more people to record their writing movement data
- learn the styles of different demonstrators and create stylistic letters based on standard letters
- implement our algorithm on real robot system
- ……

Thank you!

Project Update

A novel robotic handwriting-learning system based on Dynamic Movement Primitives (DMP)

PI: Matthew Gombolay
Student: Jing Wu, Qian Luo

1 Project Description/Current Progress

In this project, our goal is to design a robot learning system which could capture human's handwriting trajectories(demonstration) and learn from them to create its own handwriting trajectories. There are two stages in the project. In the first stage the robot will precisely imitate human's certain handwriting trajectory. In the second stage the robot will learn the śtyleóf human's handwriting trajectory and create its own trajectory based on a standard one. We have successfully accomplished the goal in the first stage with our modified DMP algorithm. Firstly, we used motion capture hardware system to collect human handwriting data. Then we input the data to our modified DMP algorithm to generate the model and specific. In this project update, we will analyze our learned trajectories to show the efficiency of our modified DMP algorithm.

2 DMP Modification

Due to the complexity of demonstrated handwriting trajectories and the existence of noise, the imitation results were not satisfying by using original DMP algorithm. Thus, we modified the original algorithm to improve its stability and flexibility. To enhance the accuracy of the DMP, we implement two major modifications of original DMP. Firstly, we use a truncated version of DMP by substituting Ψ_i as:

$$\Psi_i = \begin{cases} \exp(-\frac{h_i}{2}(x-c_i)^2), & \text{if } x-c_i \leq \theta_i \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

The advantage of using truncated kernels is that it limits the number of kernels affected by trajectory modification. That's to say, every kernel works more independently, allowing the weights of each kernel more characteristic. Secondly, we replace the exponential decay system:

$$\dot{x} = -\alpha_x x \tag{2}$$

with a linear decay system:

$$\dot{x} = -1/T \tag{3}$$

The advantage of using linear decay system is: The desired magnitude of weights of terminal kernels(as x close to 0) are significantly less. It means that, in linear decay system, it is more possible to fit curves near the endpoint.

3 Experiment

The platform we use to locate the position of our pen is a motion capture equipment, which consists of eight laser emitters and a laser reflection sensor on the pen. We use this set of equipment for collecting data as our 'target trajectory', which is exactly the way human teachers write. We collected the writing trajectories of the letter. Then we generated new trajectories using our modified DMP algorithm. The comparison outcomes shown in PowerPoint demonstrates the superiority of our algorithm against the original one.

4 Conclusion/Next Steps

In short, we have successfully imitated the writing trajectories from human demonstration. Our next steps are: 1)For the data-set part, to collect more demonstrations from human, we will invite about 15 people to write down different letters and record their movement data. 2)We will try to learn the styles of different demonstrators and create stylistic letters based on standard letters.3)If time permits, we will implement our algorithm on real robot system to see the outcomes.