Monte Carlo Method in Image Segmentation

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Introduction

[1] Angelova, D. , & Mihaylova, L. . (2011). *Contour segmentation in 2D ultrasound medical images with particle filtering*. Springer-Verlag New York, Inc.

[2] Erdil, E. , Yıldırım, Sinan, Çetin, Müjdat, & Taşdizen, Tolga. (2016). Mcmc shape sampling for image segmentation with nonparametric shape priors.

- Why I choose these two papers?
- Why is it interesting and important?

Partition the image into meaningful (homogeneous) regions.

How these two papers are related:

They both need prior information about object shape.

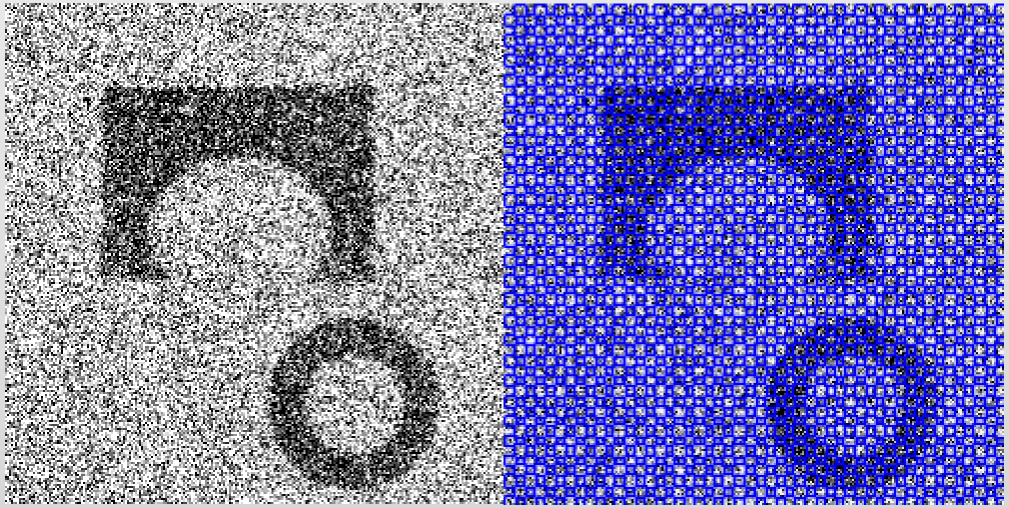
They both based on Monte Carlo Algorithm.

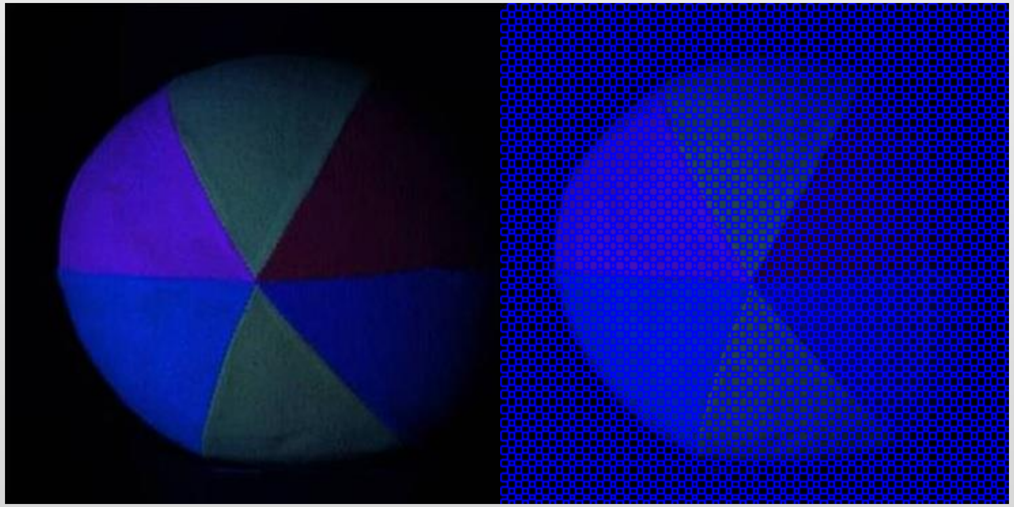
They both want to combine shape information and data in a Bayesian framework.

They both based on active contours.

They both aim to do segmentation in complicated images.

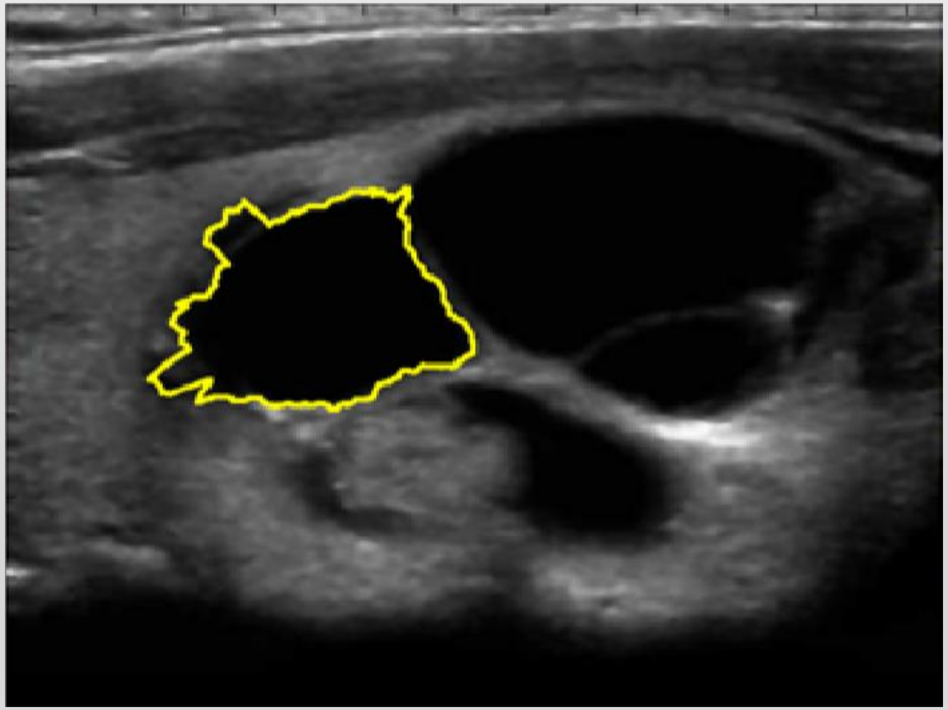
Background: Active Contours, Snakes

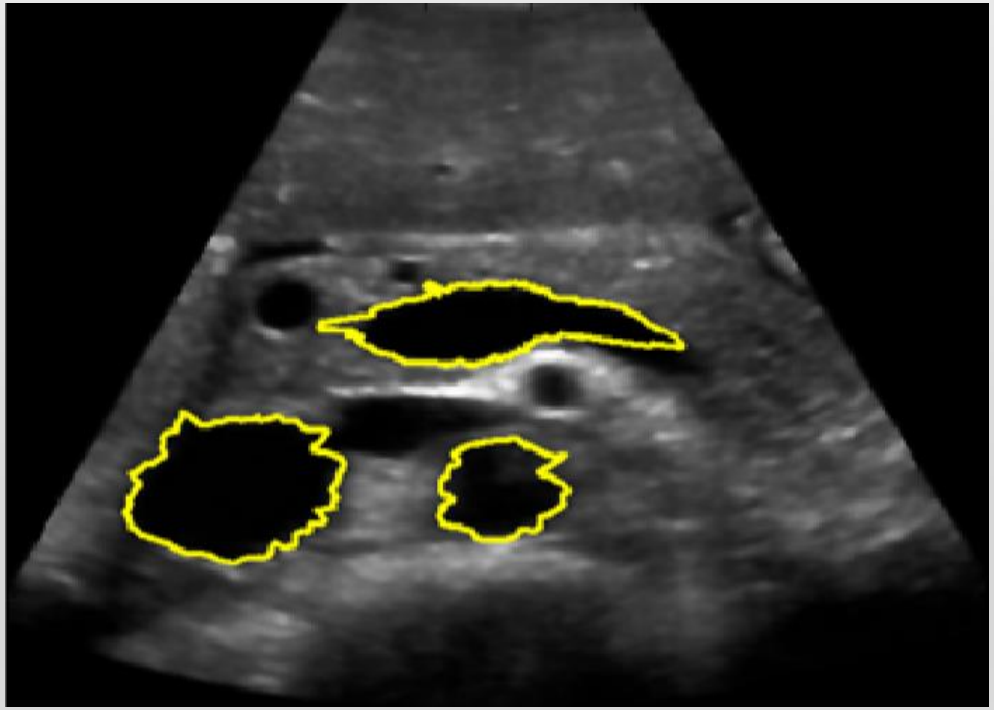




Contour segmentation in 2D ultrasound medical images with particle filtering

- Goal: Extracting lesion contours in ultrasound medical images.





Method including 3 steps

Pre-processing
- Non-linear Gaussian Filter
- Edge Preserving Diffusion

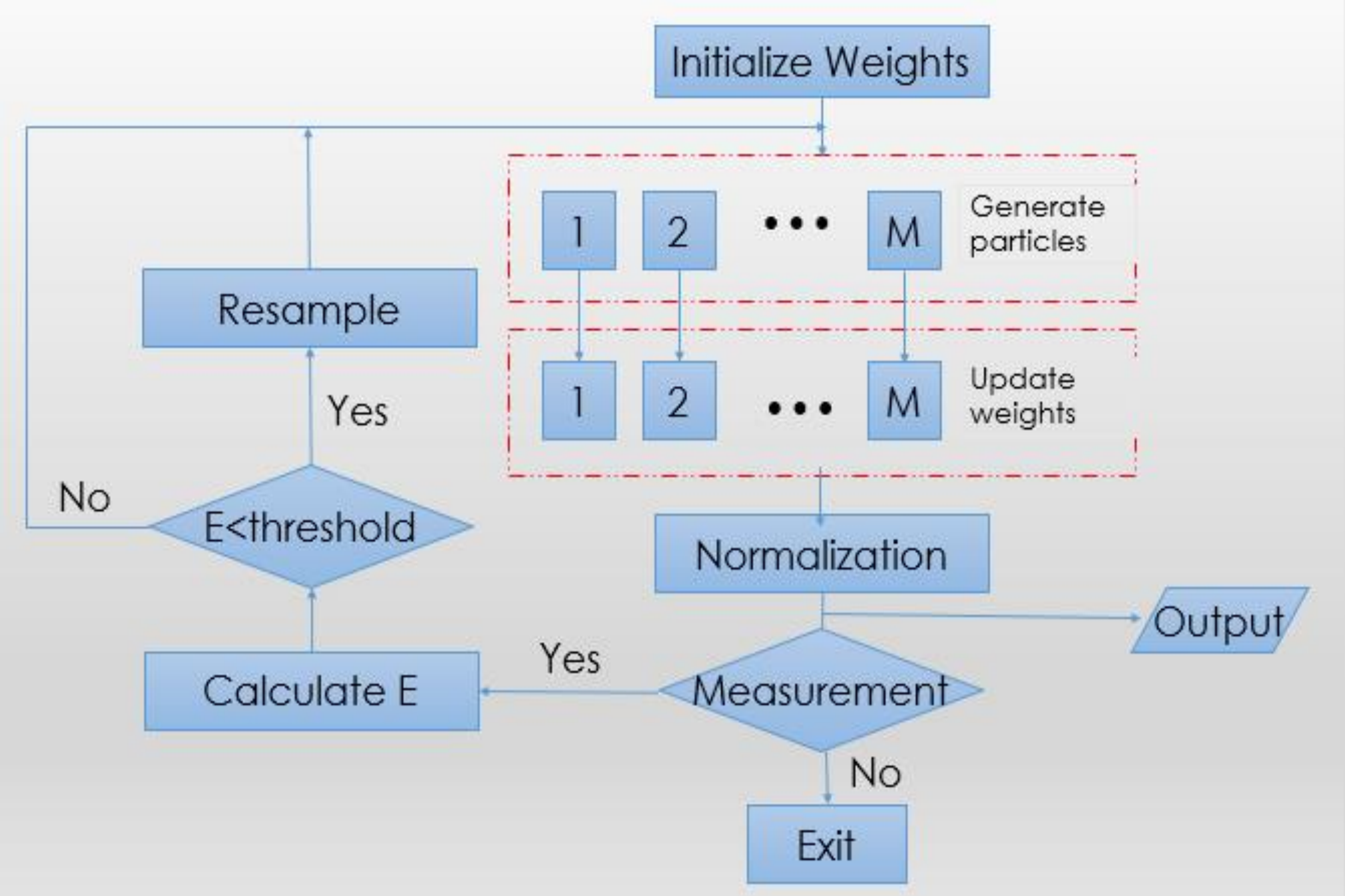
Particle Filtering
- Multiple Model Particle Filter
- Recursive Implementation

Smoothing
- Standard moving average

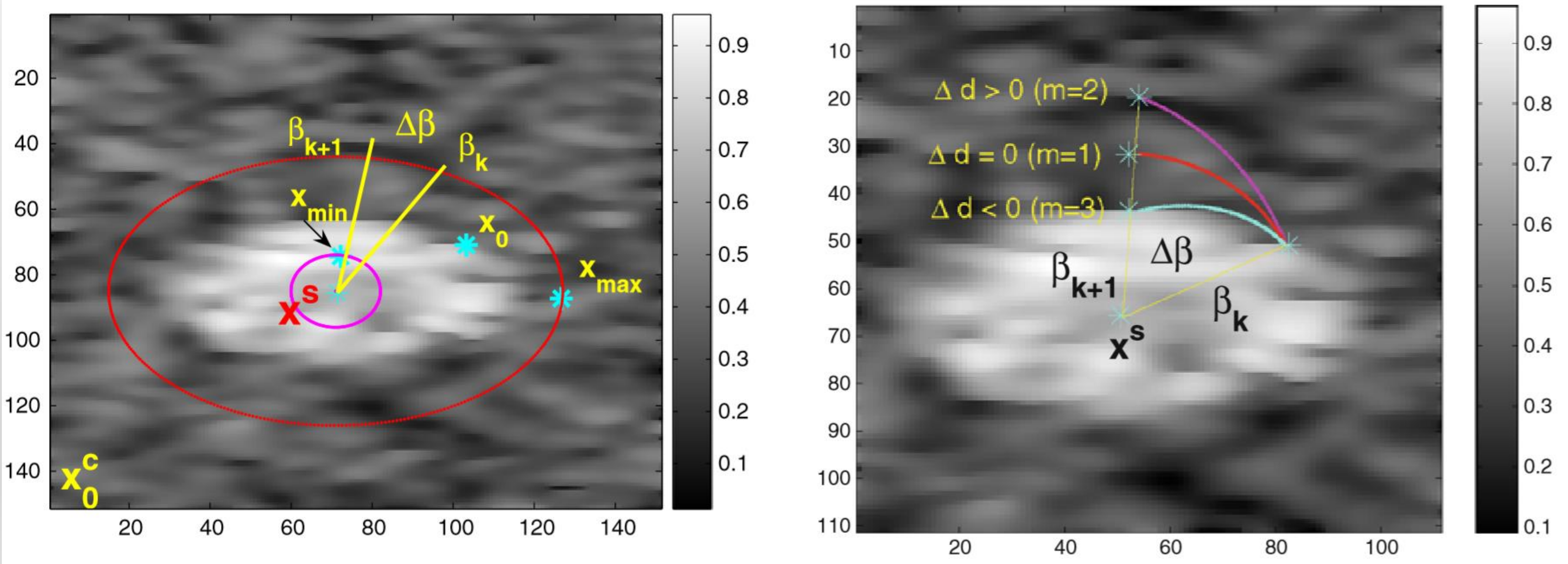
Key point: MMPF

Particle Filter

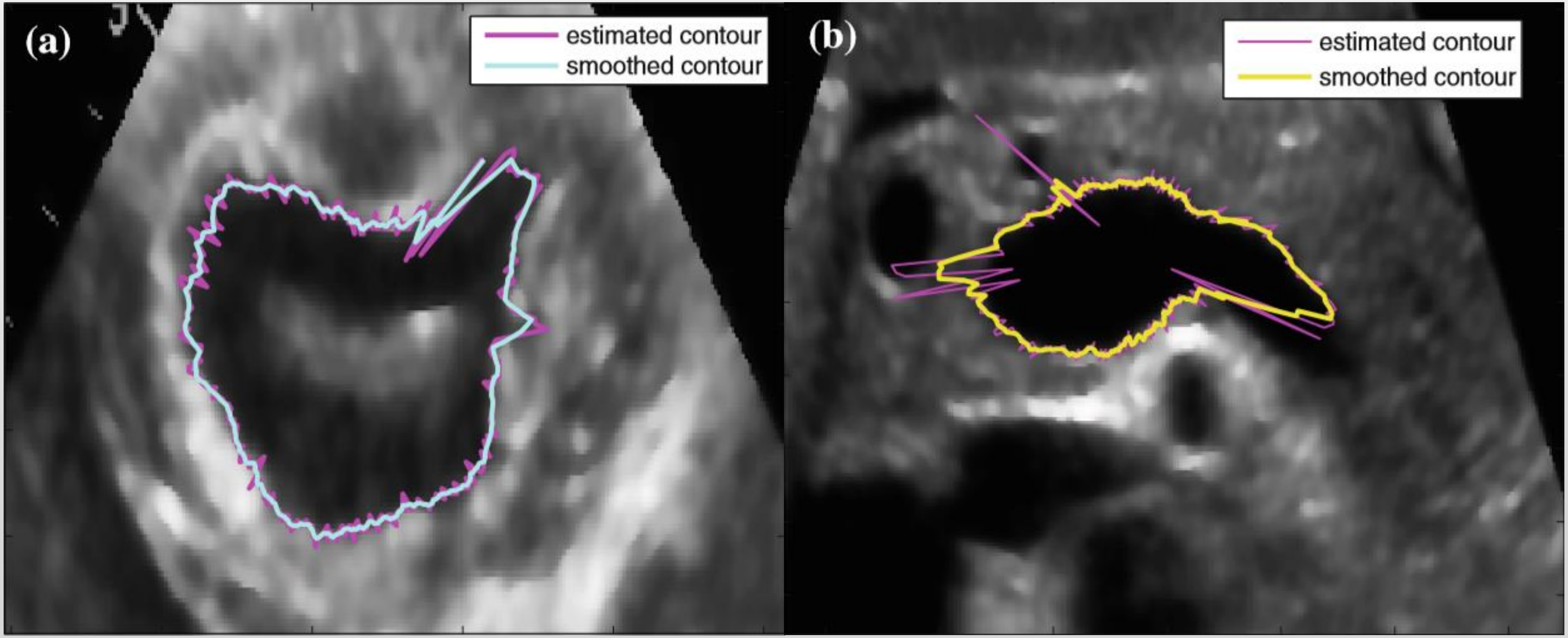
- Particles
- Measurement Space
- State Space



Particle Filter (MMPF)



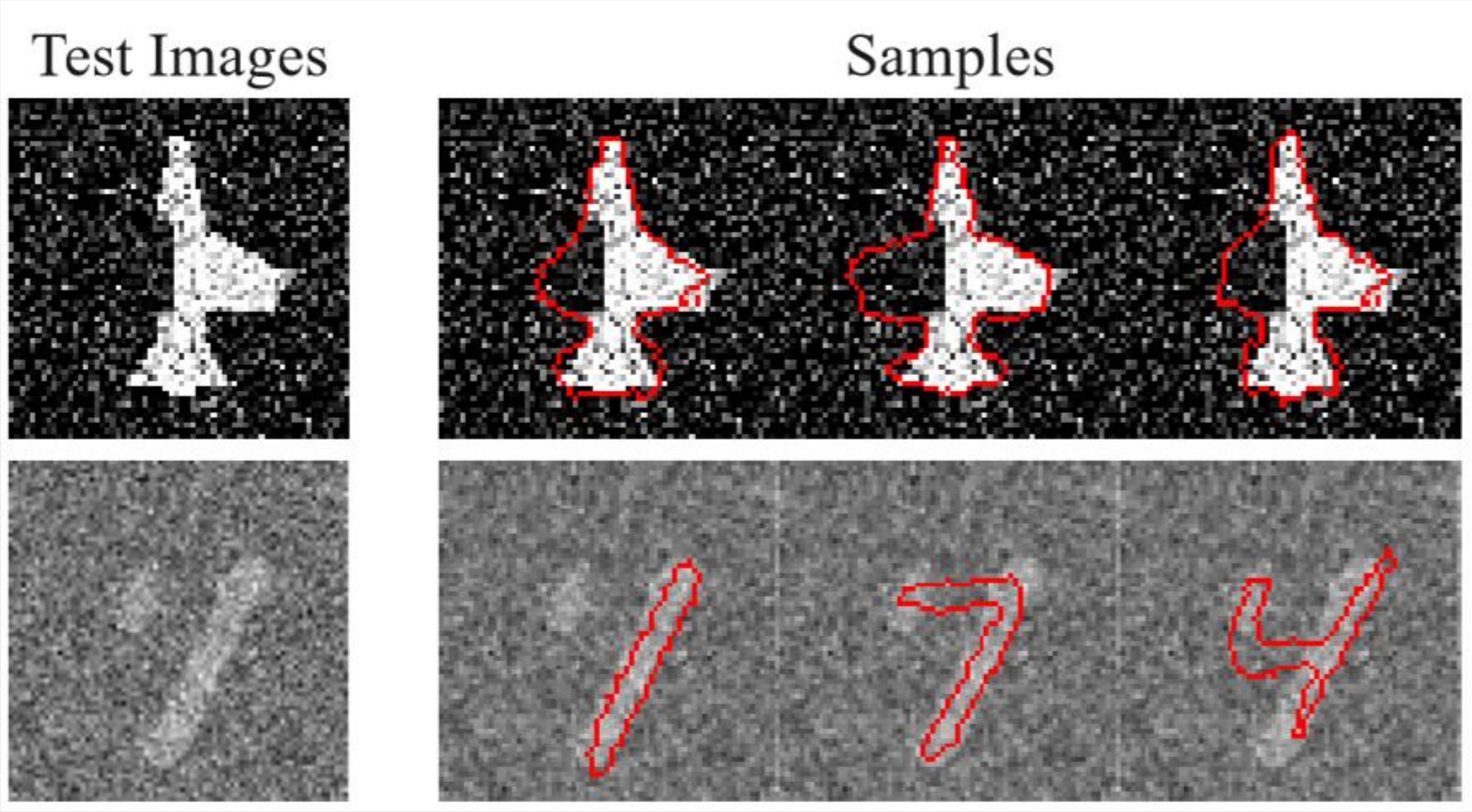
Results



(a)
estimated contour
smoothed contour
(b)
estimated contour
smoothed contour

MCMC Shape Sampling for Image Segmentation with Nonparametric Shape Priors

- Goal: segment image with occluded objects or low-quality images.



Method including 3 steps

Initial Curve
- providing initial curve
- curve evolution with data term

Data-loader
- construct level set representation of shapes in training set

Training
- MCMC shape sampling
- Metropolis-Hastings sampling

Key point: MCMC using Metropolis-Hastings sampling

Metropolis–hastings Algorithm

Algorithm 1 MCMC Shape Sampling

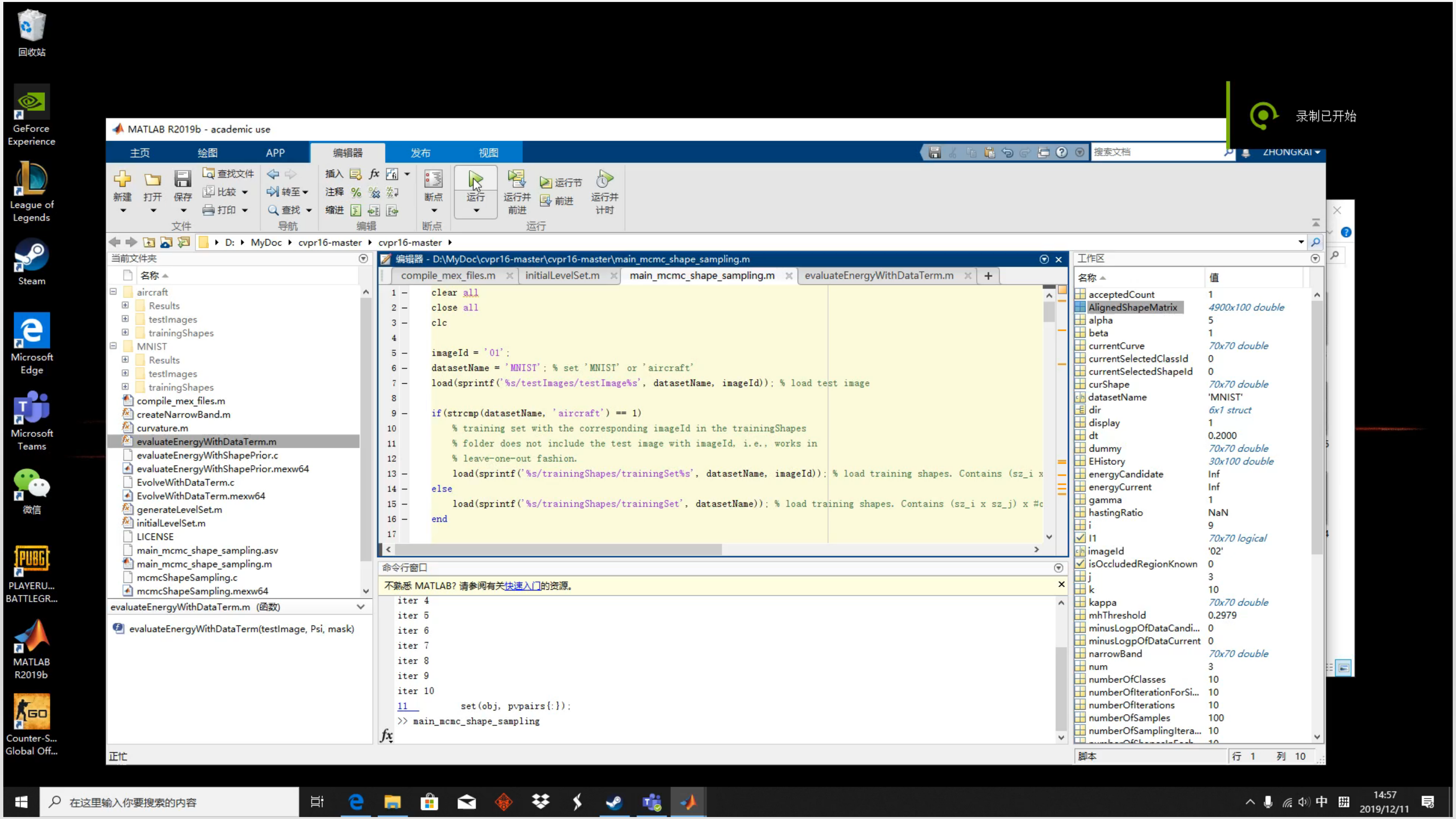
1: **for** $i = 1 \rightarrow M$ **do** ▷ M : # of samples to be generated
2: Randomly select class of $C^{(0)}$ as introduced in Section 4.1.
3: **for** $t = 0 \rightarrow (N-1)$ **do** ▷ N : # of sampling iterations
4: Generate candidate sample $\tilde{\mathcal{C}}^{(t+1)}$ from curve $\tilde{C}^{(t)}$ as introduced in Section 4.2.
▷ The steps between 5 - 10 are introduced in Section 4.3
5: Calculate Metropolis-Hastings ratio, Pr
6: $\eta = \mathcal{U}_{[0,1]}$
7: **if** $(t+1) = 1$ OR $\eta < Pr$ **then**
8: $\tilde{C}^{(t+1)} = \tilde{\mathcal{C}}^{(t+1)}$ ▷ Accept the candidate
9: **else**
10: $\tilde{C}^{(t+1)} = \tilde{C}^{(t)}$ ▷ Reject the candidate
11: **end if**
12: **end for**
13: **end for**

$$Pr\left[C^{(t+1)} = \mathcal{C}^{(t+1)} | C^{(t)}\right] = \min\left[\underbrace{\frac{\pi(\mathcal{C}^{(t+1)})}{\pi(C^{(t)})} \cdot \frac{q(C^{(t)}|\mathcal{C}^{(t+1)})}{q(\mathcal{C}^{(t+1)}|C^{(t)})}}_{\text{Metropolis-Hastings ratio}}, 1\right]$$

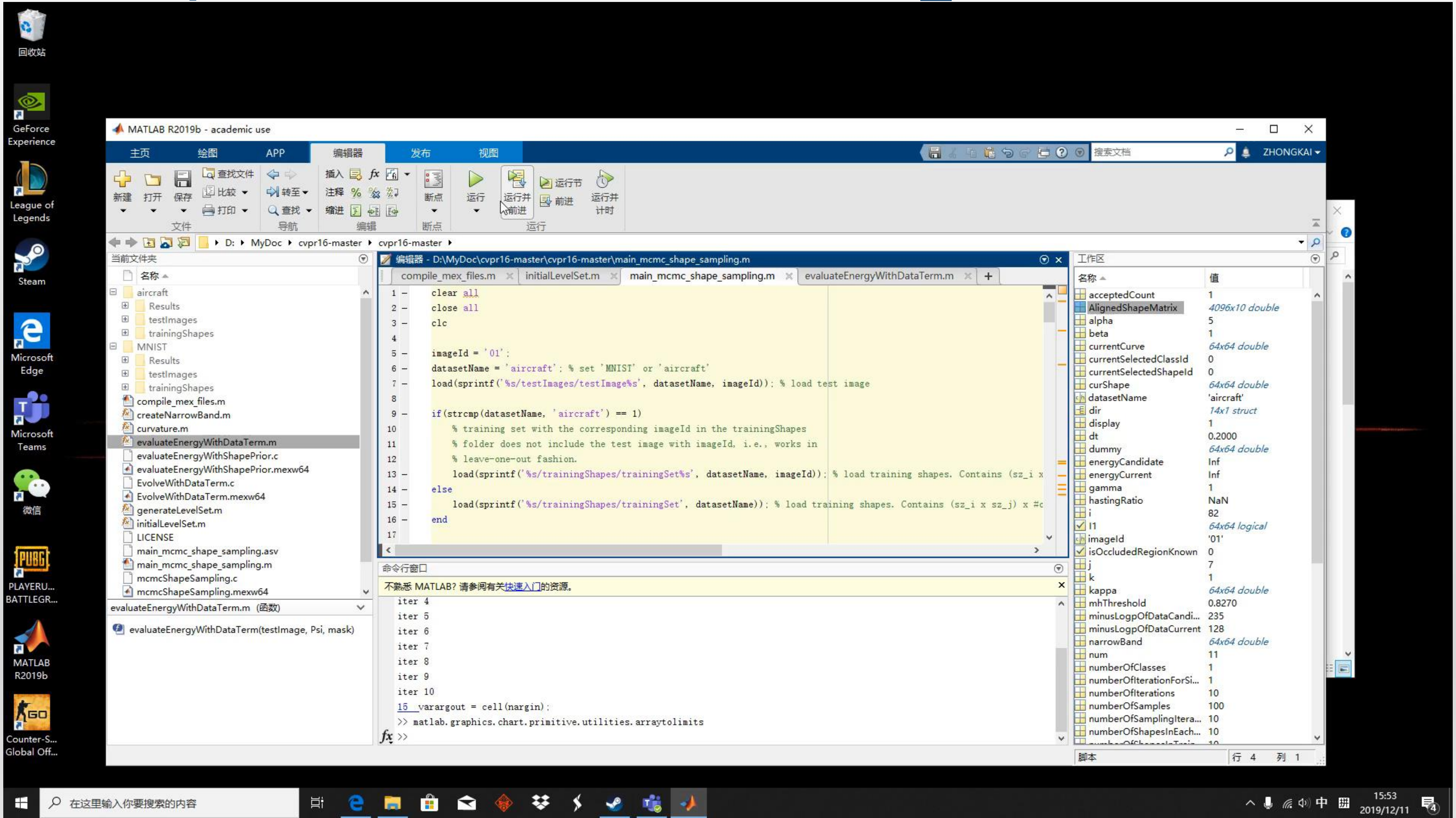
Implementation (Code)

- 1. Load the data (train & test).
- 2. Providing initial curve.
- 3. Construct level set representation of shapes in training set.
- 4. Curve evolution with data term.
- 5. MCMC shape sampling.

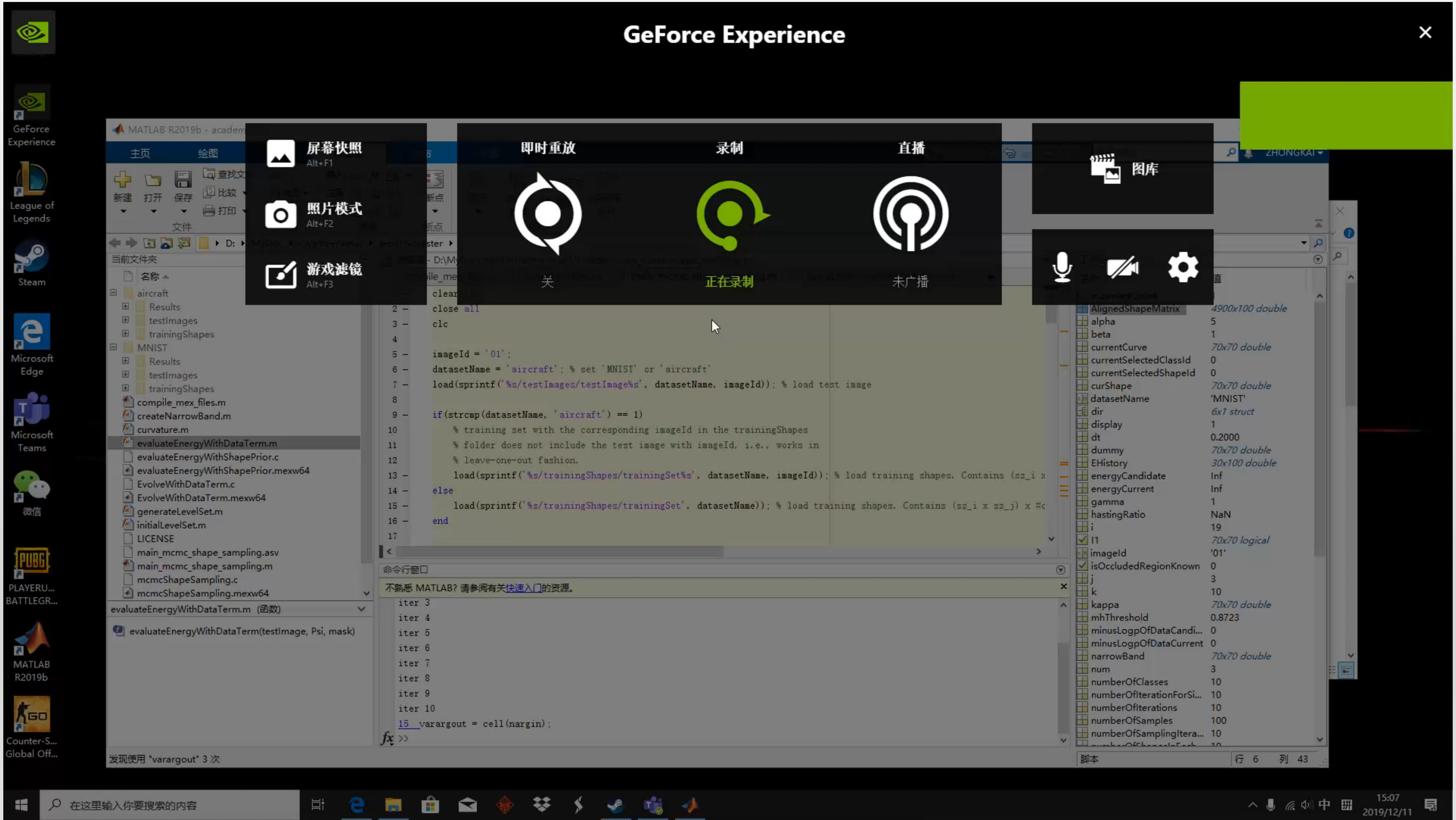
Implementation (MNIST)



Implementation (Aircraft_1)



Implementation (Aircraft_2)



Implementation

15 epochs with right prior information

100 epochs with wrong prior information

Comparison

- **Commons**:
- 1. Based on MC method.
- 2. Using active contours
- 3. Need prior information about object shape.
- **Limitation**:
- 1. Heavily rely on the prior shape information.
- 2. Hard to balance time and accuracy.

- **Difference**:

Paper One	Paper Two
Initialized with 4 points.	Generate a curve based on a given seed point.
Direct sample.	Metropolis-Hastings sample.
Segment with one class.	Segment for multi-classes(MNIST).

Comments & Contributions

- First Paper:
- 1. Proposed a Multiple Model Particle Filter structure.
- 2. Incorporation of constraints accounting for the contour convexity, which is an improvement from another method JetStream.

- Second Paper:
- 1. Better characterization of the statistical structure of the problem.
- 2. Have the potential to address issues with getting stuck at local optima.
- 3. Being able to find multiple probable solutions from different modes of the shape density.
- 4. Can deal with the missing data.

Expectations in the future.

- 1. Improve the update strategy, make the MC process converge faster or less computational.
- 2. Combine MC method with DNN.
- 3. Go to reinforcement learning.
- 4. Apply to bigger images with multiple types.

Questions?

Thank you!