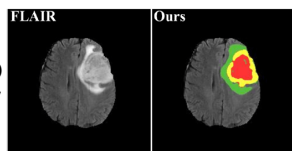


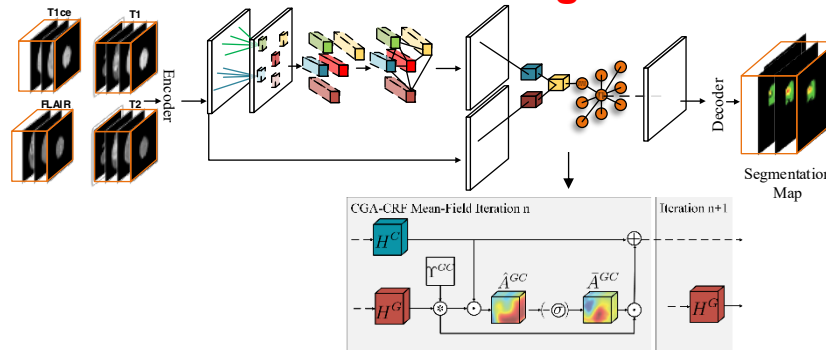


Overview

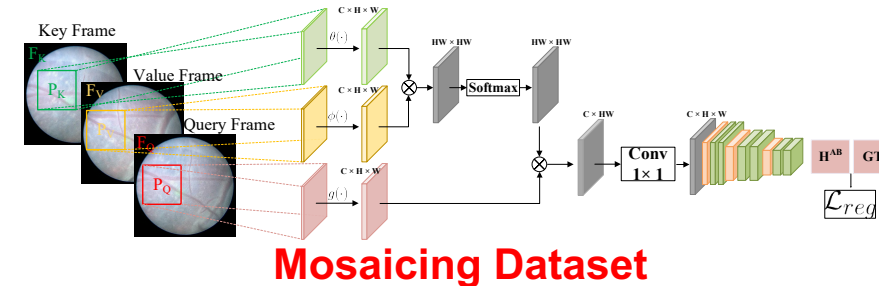
- It is very challenging to fully utilize the **relational information** (the relationship between tissues or organs or images)
- We propose two paradigms of deep relational learning called **implicit and explicit deep relational learning**.
- Case study: Brain glioma segmentation and Fetoscopy image mosaicing



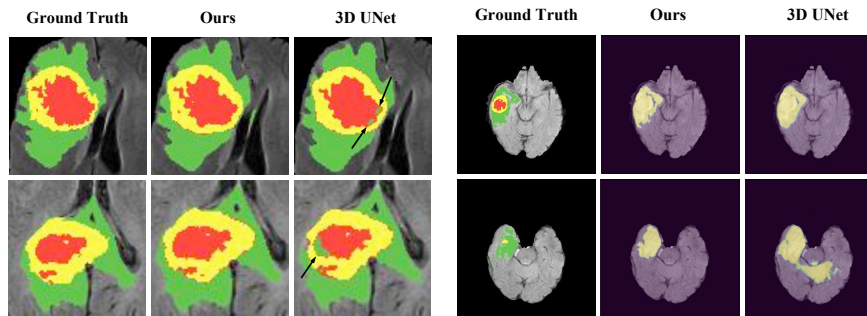
CANet: Brain Glioma Segmentation



HHEN: Fetoscopy Image Mosaicing

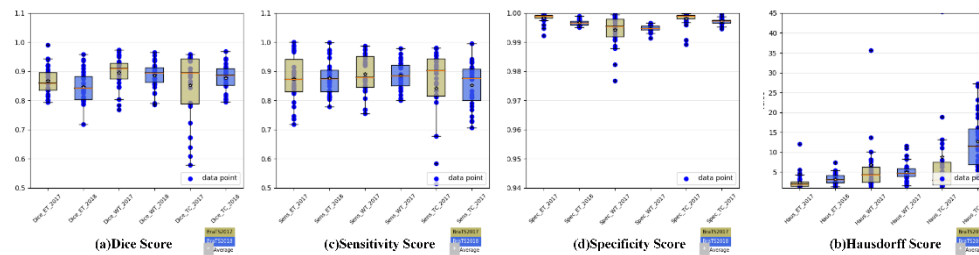


Segmentation Result Comparison



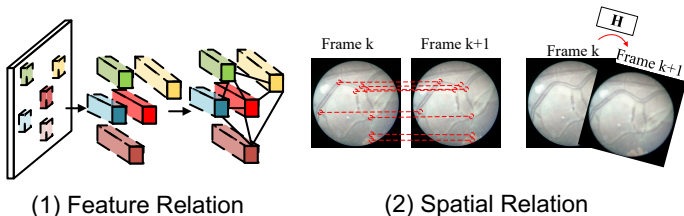
Left: Glioma segmentation result comparison. Right: Segmentation probability map visualization

Segmentation Quantitative Comparison



Box-plot of individual case segmentation score (from left to right: dice, sensitivity, specificity, hausdorff distance).

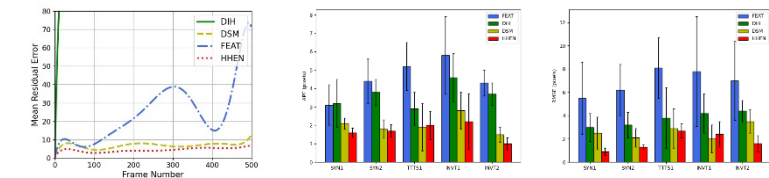
Relation Learning is Important



- Implicit relation:** Update the intermediate feature representation by considering the **neighbouring feature instances**.
- Explicit relation:** Match the **physical spatial relation** (angle, position etc) between organs/tissues in different images.
- Data-Driven:** The relational information is automatically learned from the data, **without** any hand-crafted feature engineering.
- Differentiable:** We formulate the relational learning procedure as convolutional operations, which can be **jointly trained** with any neural network backbone.

Frame Example					
Data Type	Synthetic (SYN1)	Synthetic (SYN2)	TTTS Phantom in water (TTTS1)	In-vivo TTTS Procedure (INVT1)	In-vivo TTTS Procedure (INVT2)
Total Frame Num	500	200	200	400	100
Image Resolution	500 x 500	500 x 500	600 x 600	448 x 448	448 x 448
Camera View	Planar	Planar	Planar	Non Planar	Planar
Motion Type	Spiral	Circular	Circular	Exploratory Freehand	Exploratory Freehand

Comparison on MSE/RMSE/AP



From left to right: MSE against frame number rising, RMSE comparison and AP comparison.

Trajectory Validation

