Deformable models and Geodesic Methods

Automatic liver segmentation by integrating fully convolutional networks into active contour models

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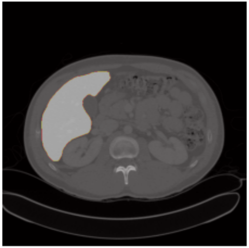
Problem statement

- Liver segmentation is a crucial step in liver surgery planning and monitoring
- Manual segmentation is time-consuming and prone to errors
- Accurate liver segmentation is a challenging task due to the liver's complex shape and the presence of other organs with similar intensities (stomach, heart)



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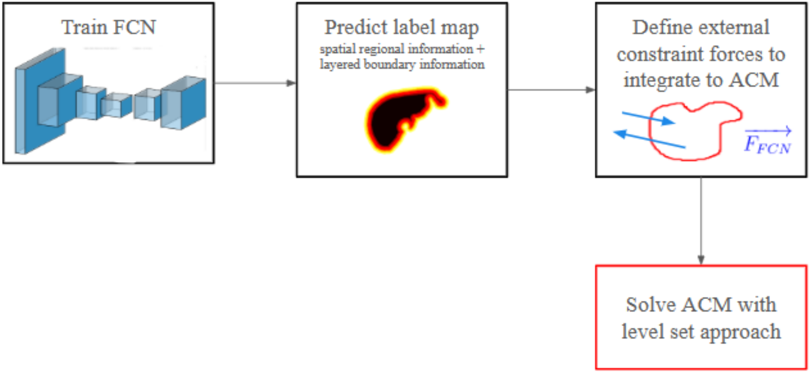
4. Conclusion and Perspectives

Convolutional Neural Networks → poor localization around object boundaries

Active Contour Models → sensitive to initialization, but topologically flexible

Integrated approach → incorporating both high-level and low-level image information

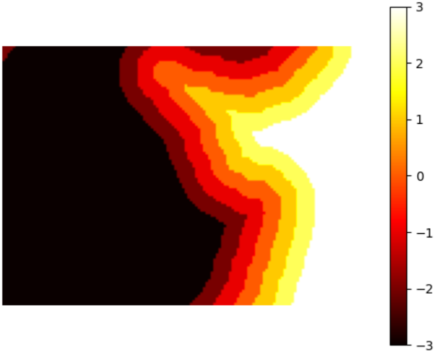


Guo et al., "Automatic liver segmentation by integrating fully convolutional networks into active contour models", 2019

Generate layered label map containing rich information

For 7 layers

$$L_{-3} = \{X | \infty < \varphi(X) < -2.5\delta\}$$
$$L_{-2} = \{X | -2.5\delta < \varphi(X) \leq -1.5\delta\}$$
$$L_{-1} = \{X | -1.5\delta < \varphi(X) \leq -0.5\delta\}$$
$$L_{0} = \{X | -0.5\delta < \varphi(X) \leq 0.5\delta\}$$
$$L_{1} = \{X | 0.5\delta < \varphi(X) \leq 1.5\delta\}$$
$$L_{2} = \{X | 1.5\delta < \varphi(X) \leq 2.5\delta\}$$
$$L_{3} = \{X | 2.5\delta < \varphi(X) \leq \infty\}$$

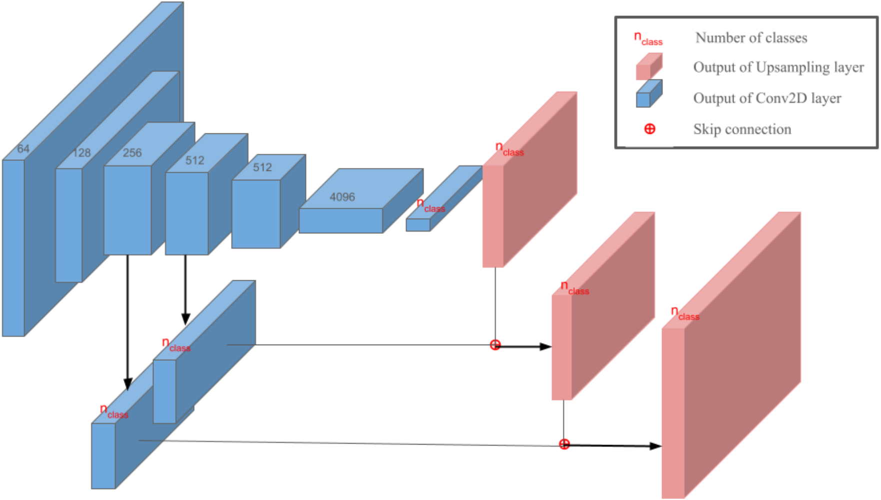


$\delta = d/\mathrm{ps}$ is a parameter to control narrow bandwidth, ps is the pixel spacing and d is the bandwidth in millimeters

$d = 5$

Train FCN to predict layered label map

Pre-trained model FCN-8 on the PASCAL dataset (21 classes)



Long et al., *Fully Convolutional Networks for Semantic Segmentation*, 2015

Let φ be a Lipschitz function
Evolving the curve $C = \{(x, y), \quad \varphi(x, y) = 0\}$ in the normal direction with speed V amount to solve

$$\begin{cases} \frac{\partial \varphi}{\partial t} = V \, \|\nabla \varphi\| \\ \varphi(0, x, y) = \varphi_0(x, y) \end{cases}$$

φ_0 is the signed distance to the initial contour defined by the user

Chan et al., "Active contours without edges", 2001

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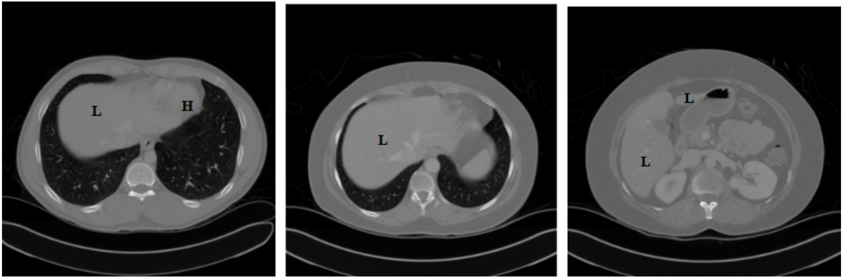
CHAOS Dataset

Kavur et al., *CHAOS - Combined (CT-MR) Healthy Abdominal Organ Segmentation Challenge Data*, 2019

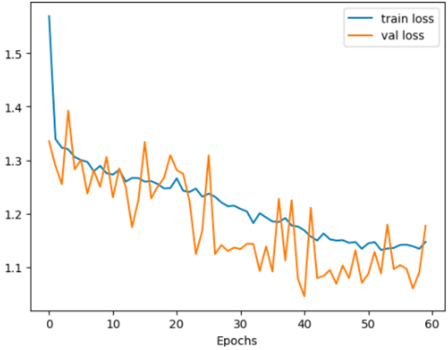
- 512×512 CT images of 20 different patients with healthy liver (no tumor, lesions or any other diseases)
- For each patient, there is a series of DICOM images ($\sim$100 slices per patient)
- A dataset with challenges : partial volume effects, atypical liver shapes, etc.



(a) Atypical shape (b) Unclear boundary (c) Disconnected parts

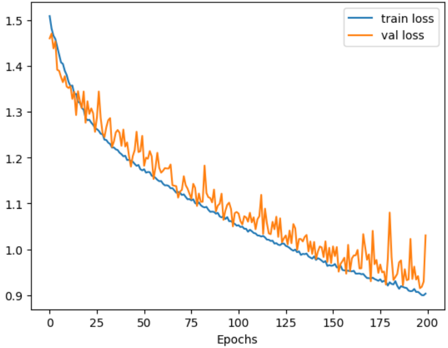
Train FCN

Transfer learning with pre-trained FCN-8 weights from Long et al.



(1) Train only the new layers

Batch size of 20, use of Cosine Annealing Learning Rate Scheduler from lr = 0.005



(2) Unfreeze some pre-trained layers

(the last 9)

Batch size of 16, lr = 0.0001

2005 training images, 200 epochs, SGD optimizer with momentum of .9

The early stopper was never reached

$\frac{\partial \varphi}{\partial t} = G(\varphi)$

Algorithm Level Set Method

Input

I	(Normalized) Image
φ_0	Signed distance to the initial contour
N	Number of iterations
δt	Step size
n	Re-distancing period

Initialize $\varphi^{(0)} \leftarrow \varphi_0$

for $t = 0$ to N **do**

Compute $G(\varphi^{(t)})$

$\varphi^{(t+1)} \leftarrow \varphi^{(t)} - \delta t \; G(\varphi^{(t)})$ ▷ Gradient Descent

Re-distancing $\varphi^{(t+1)}$ every n iterations ▷ Levelset Re-distancing

end for

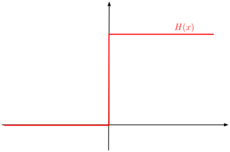
Comparative Evaluation

Mean Curvature Motion with global regional Chan Vese forces

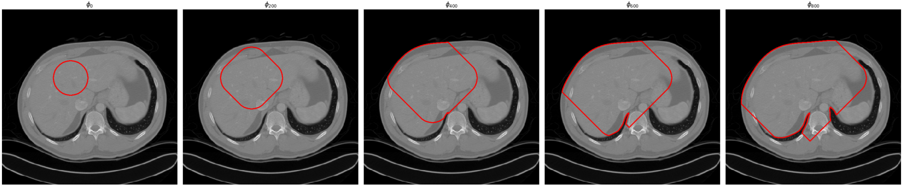
$$G(\varphi) = \omega_0 \|\nabla\varphi\| \,\mathrm{div}\left(\frac{\nabla\varphi}{\|\nabla\varphi\|}\right) + \omega_1((I - c_{\mathrm{ext}})^2 - (I - c_{\mathrm{int}})^2)$$

$$c_{\mathrm{int}} = \frac{\int_\Omega I(x)(1 - H(\varphi(x)))dx}{\int_\Omega 1 - H(\varphi(x))dx}$$

$$c_{\mathrm{ext}} = \frac{\int_\Omega I(x)H(\varphi(x))dx}{\int_\Omega H(\varphi(x))dx}$$



1000 iterations, $\omega_0 = 0.001$, $\omega_1 = 5$, $\delta t = 0.4$



Comparative Evaluation

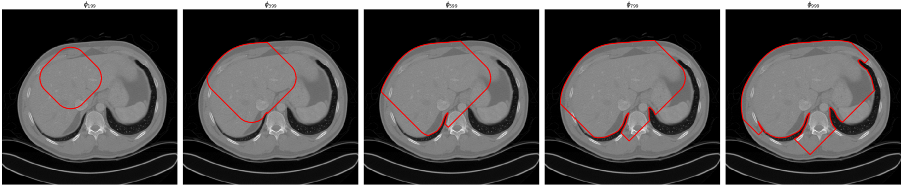
Mean Curvature Motion with global regional Chan Vese forces with edge information

Caselles et al., "Geodesic Active Contours", 1997

$$G(\varphi) = \omega_0 g(I)\,\|\nabla\varphi\|\,\mathrm{div}\left(\frac{\nabla\varphi}{\|\nabla\varphi\|}\right) + \omega_0\langle\nabla g, \nabla\varphi\rangle + \omega_1 F_{CV}$$

$$g(I) = \frac{1}{\epsilon + \|\nabla\ k_\sigma * I\|}$$

1000 iterations, $\omega_0 = 0.001$, $\omega_1 = 5$, $\delta t = 0.4$

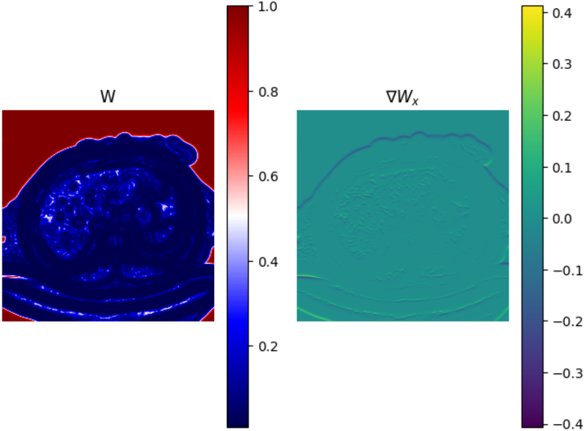


Comparative Evaluation

Adding Edge Information

Caselles et al., "Geodesic Active Contours", 1997

$$W = g(I) = \frac{1}{\epsilon + \|\nabla \ k_\sigma * I\|}$$



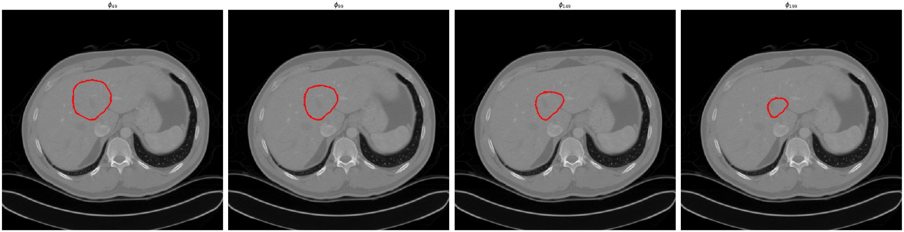
Lankton et al., "Localizing Region-Based Active Contours", 2008

$$G(\varphi) = \omega_0 \|\nabla\varphi\| \operatorname{div}\left(\frac{\nabla\varphi}{\|\nabla\varphi\|}\right) + \omega_1((I - c_{\text{ext},x})^2 - (I - c_{\text{int},x})^2)$$

$$B_r(x,y) = \mathbb{1}_{\|x-y\|\leq r}$$

$$c_{\text{int},x} = \frac{\int_\Omega B_r(x,y)I(y)(1-H(\varphi(y)))dy}{\int_\Omega B_r(x,y)(1-H(\varphi(y)))dy} \qquad c_{\text{ext},x} = \frac{\int_\Omega B_r(x,y)I(y)H(\varphi(y))dy}{\int_\Omega B_r(x,y).H(\varphi(y))dy}$$

200 iterations, $\omega_0 = 0.1$, $\omega_1 = 5$, $\delta t = 0.4$, $r = 10$



Comparative Evaluation

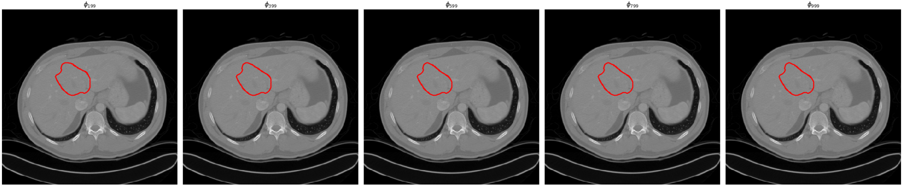
Mean Curvature Motion with local regional Chan Vese forces with edge information

Caselles et al., "Geodesic Active Contours", 1997

$$G(\varphi) = \omega_0 g(I)\,\|\nabla\varphi\|\,\mathrm{div}\left(\frac{\nabla\varphi}{\|\nabla\varphi\|}\right) + \omega_0\langle\nabla g, \nabla\varphi\rangle + \omega_1 F_{CV,x}$$

$$g(I) = \frac{1}{\epsilon + \|\nabla\ k_\sigma * I\|}$$

1000 iterations, $\omega_0 = 0.1$, $\omega_1 = 5$, $\delta t = 0.4$, $r = 10$



Comparative Evaluation

Mean Curvature Motion with global regional Chan Vese forces with additional F_{FCN}

Guo et al., "Automatic liver segmentation by integrating fully convolutional networks into active contour models", 2019

$$G(\varphi) = \omega_0 \left\|\nabla\varphi\right\| \kappa + \omega_1 F_{CV} + \omega_2 F_{\mathrm{FCN}}$$

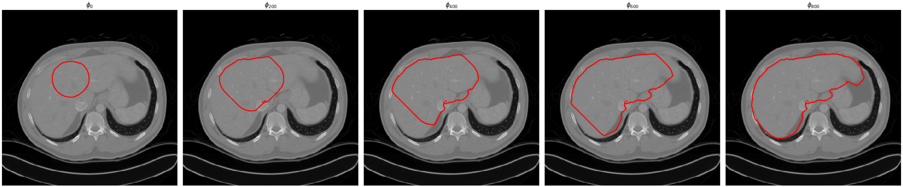
Polynomial formulation of order p

$$F_{\mathrm{FCN}} = \mathrm{sign}(L(x,y))|L(x,y)|^p \vec{n}$$

Exponential formulation

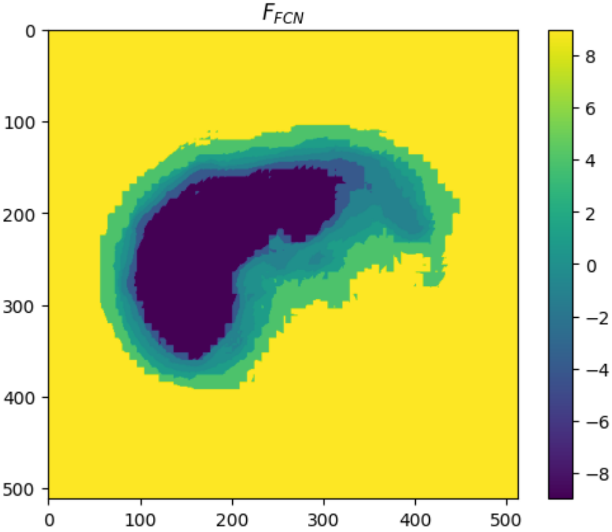
$$F_{\mathrm{FCN}} = \alpha \;.\; \mathrm{sign}(L(x,y))\mathrm{e}^{|L(x,y)|} \vec{n}$$

1000 iterations, $\omega_0 = 0.01$, $\omega_1 = 5$, $\omega_2 = 1$, $\delta t = 0.4$, $p = 2$



Comparative Evaluation
External constraint F_{FCN} forces

Polynomial function with $p = 2$

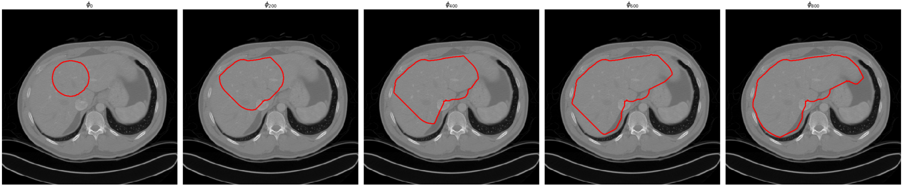


Comparative Evaluation

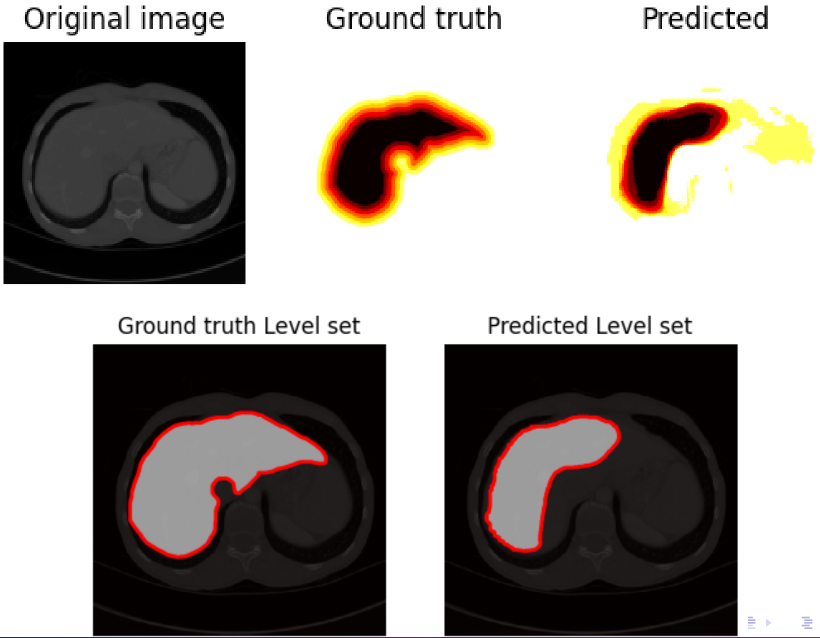
Mean Curvature Motion with local regional Chan Vese forces with additional F_{FCN}

$$G(\varphi) = \omega_0 \left\| \nabla \varphi \right\| \kappa + \omega_1 F_{CV,x} + \omega_2 F_{\mathrm{FCN}}$$

1000 iterations, $\omega_0 = 0.01$, $\omega_1 = 5$, $\omega_2 = 1$, $\delta t = 0.4$, $r = 10$, $p = 2$

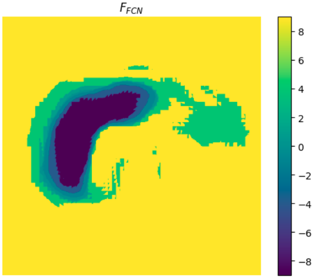


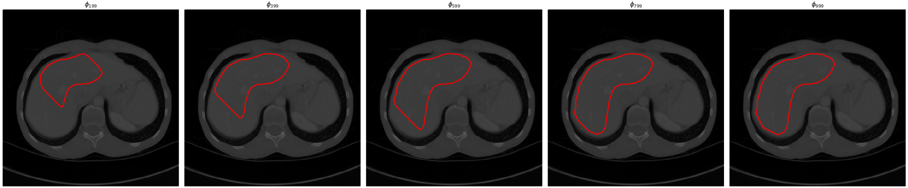
A Pathological Case



Mean Curvature Motion with global Chan Vese forces and polynomial FCN forces

1000 iterations, $\omega_0 = 0.01$, $\omega_1 = 5$, $\omega_2 = 1$, $\delta t = 0.4$, $p = 2$





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- Parallel with the Balloon model (inflation force)
- Possible improvements by using another method for level set Resolution : sparse field method [Guo et al., "Automatic liver segmentation by integrating fully convolutional networks into active contour models", 2019, Whitaker, "A Level-Set Approach to 3D Reconstruction from Range Data", 1998]
- Train with additional dataset (SLIVER07)
- Experiment with other architectures (Other FCNs [Long et al., *Fully Convolutional Networks for Semantic Segmentation*, 2015], DeepLab [Chen et al., "Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation", 2018], U-Net [Huang et al., "UNet 3+", 2020])

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