

Deformable models and Geodesic Methods

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

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1. Problem statement

2. Proposed Method

- Generate layered label map containing rich information
- Train FCN to predict layered label map
- Integrating NN's output to ACM

3. Experiments and Implementation Details

- Dataset
- Train FCN
- Solve ACM
- Comparative Analysis: Evaluating Active Contours Models
- A Pathological Case

4. Conclusion and Perspectives



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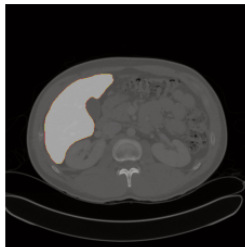
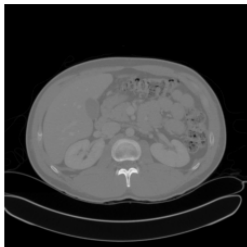
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Problem statement

- 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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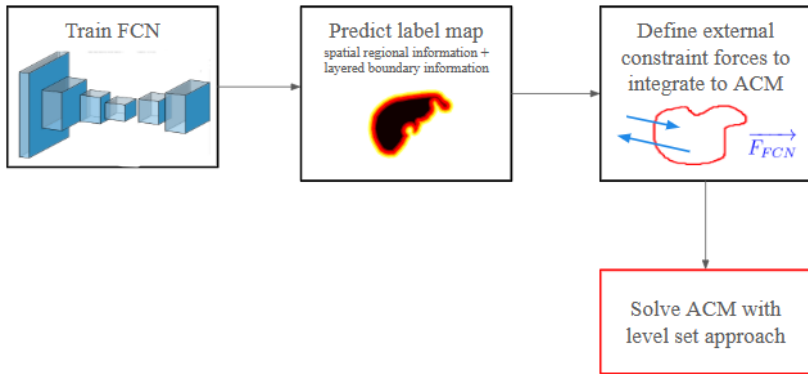


Proposed Method

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

$$L_{-3} = \{X | \infty < \varphi(X) < -2.5\delta\}$$

$$L_{-2} = \{X | -2.5\delta < \varphi(X) \leq -1.5\delta\}$$

$$L_{-1} = \{X | -1.5\delta < \varphi(X) \leq -0.5\delta\}$$

$$L_0 = \{X | -0.5\delta < \varphi(X) \leq 0.5\delta\}$$

$$L_1 = \{X | 0.5\delta < \varphi(X) \leq 1.5\delta\}$$

$$L_2 = \{X | 1.5\delta < \varphi(X) \leq 2.5\delta\}$$

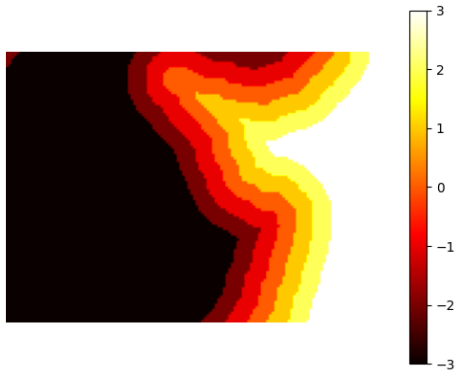
$$L_3 = \{X | 2.5\delta < \varphi(X) \leq \infty\}$$

$\delta = d/\text{ps}$ parameter to control
narrow bandwidth

ps pixel spacing

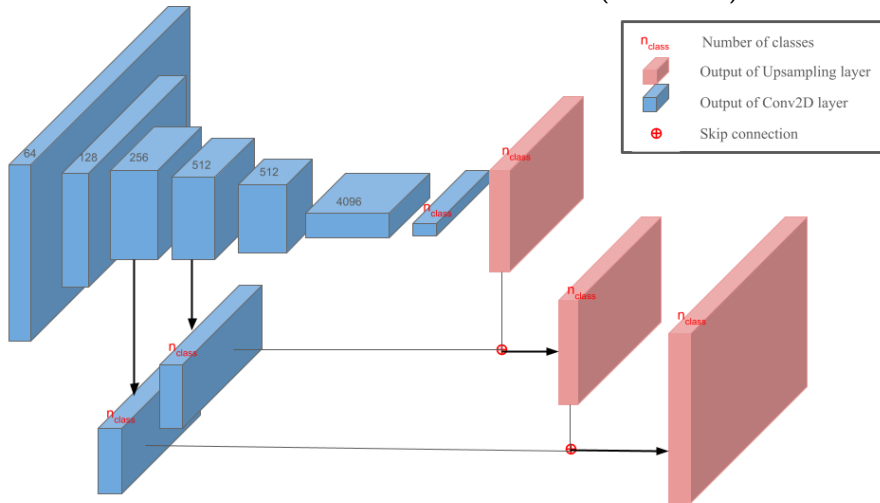
d bandwidth in millimeters

$d = 5$



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 $C = \{(x, y), \varphi(x, y) = 0\}$ 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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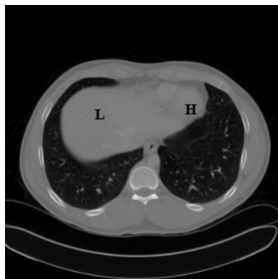
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CHAOS Dataset

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

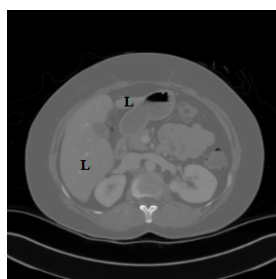
- 512×512 CT images of 20 different patients with healthy liver (no tumor, lesions or any other diseases)
- For each patient, there is a series of DICOM images (~ 100 slices per patient)
- A dataset with challenges : partial volume effects, atypical liver shapes, etc.



(a) Atypical shape



(b) Unclear boundary

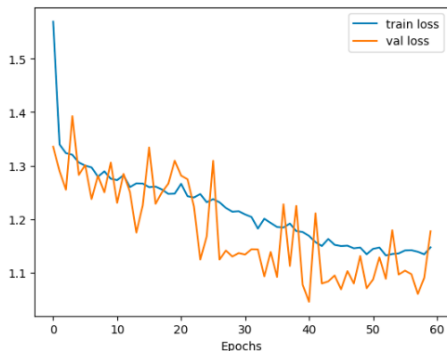


(c) Disconnected parts



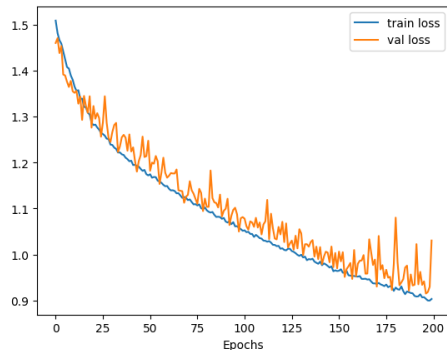
Train FCN

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

$\varphi^{(t+1)} \leftarrow \varphi^{(t)} - \delta t \, G(\varphi^{(t)})$

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

end for

- ▷ Gradient Descent
- ▷ Levelset Re-distancing



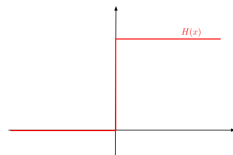
Comparative Evaluation

Mean Curvature Motion with **global** regional Chan Vese forces

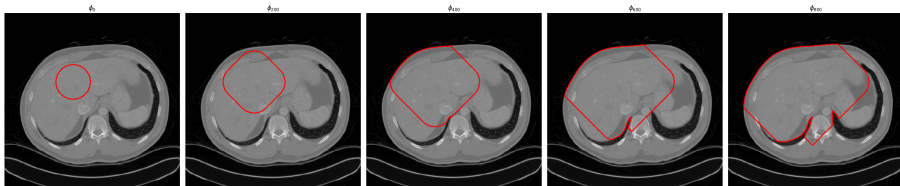
$$G(\varphi) = \omega_0 \|\nabla \varphi\| \operatorname{div} \left(\frac{\nabla \varphi}{\|\nabla \varphi\|} \right) + \omega_1 ((I - c_{\text{ext}})^2 - (I - c_{\text{int}})^2)$$

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

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



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



Comparative Evaluation

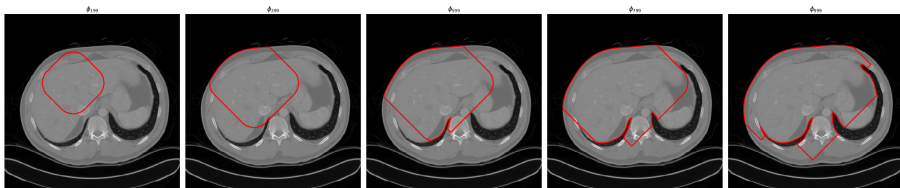
Mean Curvature Motion with **global** regional Chan Vese forces **with edge information**

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

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

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

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

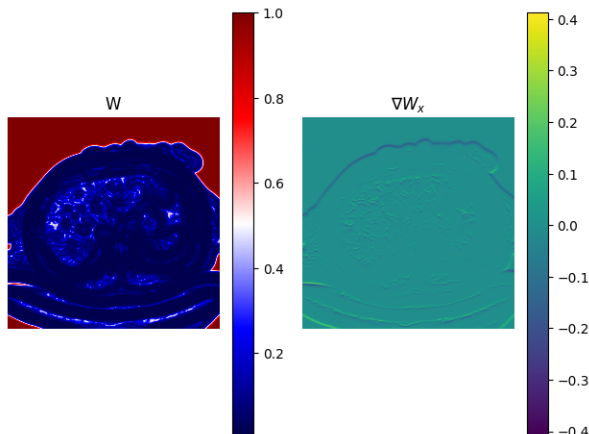


Comparative Evaluation

Adding Edge Information

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

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



Comparative Evaluation

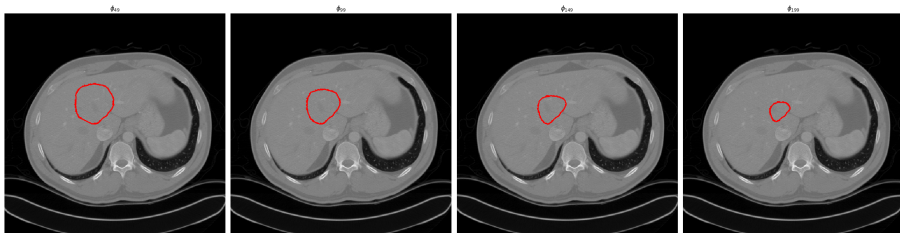
Mean Curvature Motion with **local** regional Chan Vese forces

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

$$G(\varphi) = \omega_0 \|\nabla \varphi\| \operatorname{div} \left(\frac{\nabla \varphi}{\|\nabla \varphi\|} \right) + \omega_1 ((I - c_{\text{ext},x})^2 - (I - c_{\text{int},x})^2)$$
$$B_r(x, y) = \mathbb{1}_{\|x-y\| \leq r}$$

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

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



Comparative Evaluation

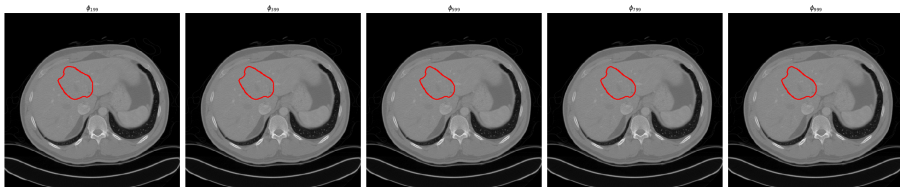
Mean Curvature Motion with **local** regional Chan Vese forces **with edge information**

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

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

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

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

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

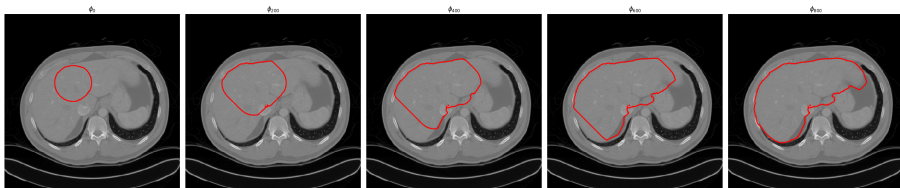
Polynomial formulation of order p

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

Exponential formulation

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

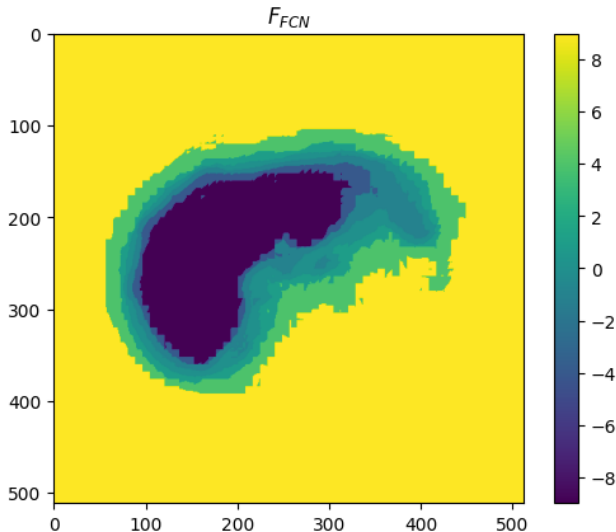
1000 iterations, $\omega_0 = 0.01$, $\omega_1 = 5$, $\omega_2 = 1$, $\delta t = 0.4$, $p = 2$



Comparative Evaluation

External constraint F_{FCN} forces

Polynomial function with $p = 2$

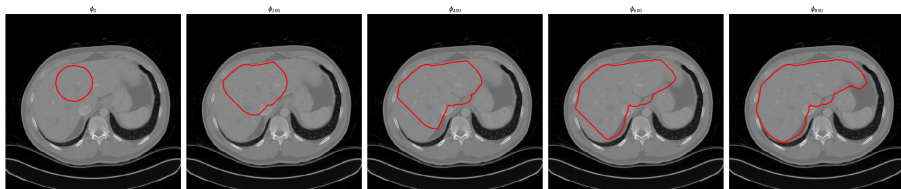


Comparative Evaluation

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

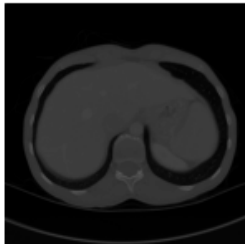
$$G(\varphi) = \omega_0 \|\nabla \varphi\| \kappa + \omega_1 F_{CV,x} + \omega_2 F_{FCN}$$

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

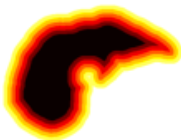


A Pathological Case

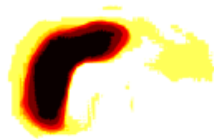
Original image



Ground truth



Predicted



Ground truth Level set



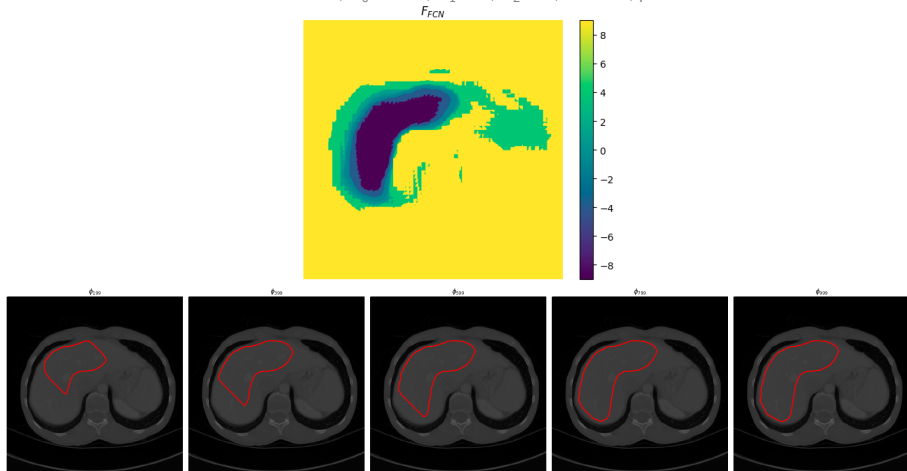
Predicted Level set



A Pathological Case - Result

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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Conclusion and Perspectives

- 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])





Caselles, Vicent, Ron Kimmel, and Guillermo Sapiro (Feb. 1, 1997). “Geodesic Active Contours”. In: *International Journal of Computer Vision* 22.1, pp. 61–79. ISSN: 1573-1405. DOI: 10.1023/A:1007979827043. URL: <https://doi.org/10.1023/A:1007979827043> (visited on 03/09/2024).



Chan, T.F. and L.A. Vese (Feb. 2001). “Active contours without edges”. In: *IEEE Transactions on Image Processing* 10.2. Conference Name: IEEE Transactions on Image Processing, pp. 266–277. ISSN: 1941-0042. DOI: 10.1109/83.902291. URL: <https://ieeexplore.ieee.org/abstract/document/902291> (visited on 03/09/2024).





Chen, Liang-Chieh et al. (2018). “Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation”. In: *Computer Vision – ECCV 2018*. Ed. by Vittorio Ferrari et al. Vol. 11211. Series Title: Lecture Notes in Computer Science. Cham: Springer International Publishing, pp. 833–851. ISBN: 978-3-030-01233-5 978-3-030-01234-2. DOI: 10.1007/978-3-030-01234-2_49. URL: https://link.springer.com/10.1007/978-3-030-01234-2_49 (visited on 03/30/2024).



Guo, Xiaotao, Lawrence H. Schwartz, and Binsheng Zhao (2019). “Automatic liver segmentation by integrating fully convolutional networks into active contour models”. In: *Medical Physics* 46.10. _eprint: <https://onlinelibrary.wiley.com/doi/pdf/10.1002/mp.13735>, pp. 4455–4469. ISSN: 2473-4209. DOI: 10.1002/mp.13735. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1002/mp.13735> (visited on 03/06/2024).





Huang, Huimin et al. (May 2020). “UNet 3+: A Full-Scale Connected UNet for Medical Image Segmentation”. In: *ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). Barcelona, Spain: IEEE, pp. 1055–1059. ISBN: 978-1-5090-6631-5. DOI: 10.1109/ICASSP40776.2020.9053405. URL: <https://ieeexplore.ieee.org/document/9053405/> (visited on 03/30/2024).



Kavur, Ali Emre et al. (Apr. 2019). *CHAOS - Combined (CT-MR) Healthy Abdominal Organ Segmentation Challenge Data*. Version v1.03. Zenodo. DOI: 10.5281/zenodo.3362844. URL: <https://doi.org/10.5281/zenodo.3362844>.





Lankton, Shawn and Allen Tannenbaum (Nov. 2008). “Localizing Region-Based Active Contours”. In: *IEEE Transactions on Image Processing* 17.11. Conference Name: IEEE Transactions on Image Processing, pp. 2029–2039. ISSN: 1941-0042. DOI: 10.1109/TIP.2008.2004611. URL: <https://ieeexplore.ieee.org/abstract/document/4636741> (visited on 03/09/2024).



Long, Jonathan, Evan Shelhamer, and Trevor Darrell (Mar. 8, 2015). *Fully Convolutional Networks for Semantic Segmentation*. arXiv: 1411.4038[cs]. URL: <http://arxiv.org/abs/1411.4038> (visited on 03/09/2024).





Whitaker, Ross T. (Sept. 1, 1998). “A Level-Set Approach to 3D Reconstruction from Range Data”. In: *International Journal of Computer Vision* 29.3, pp. 203–231. ISSN: 1573-1405. DOI: 10.1023/A:1008036829907. URL: <https://doi.org/10.1023/A:1008036829907> (visited on 03/09/2024).

