

Automated Liver segmentation in CT images using three dimensional to two dimensional fully convolutional network

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Introduction

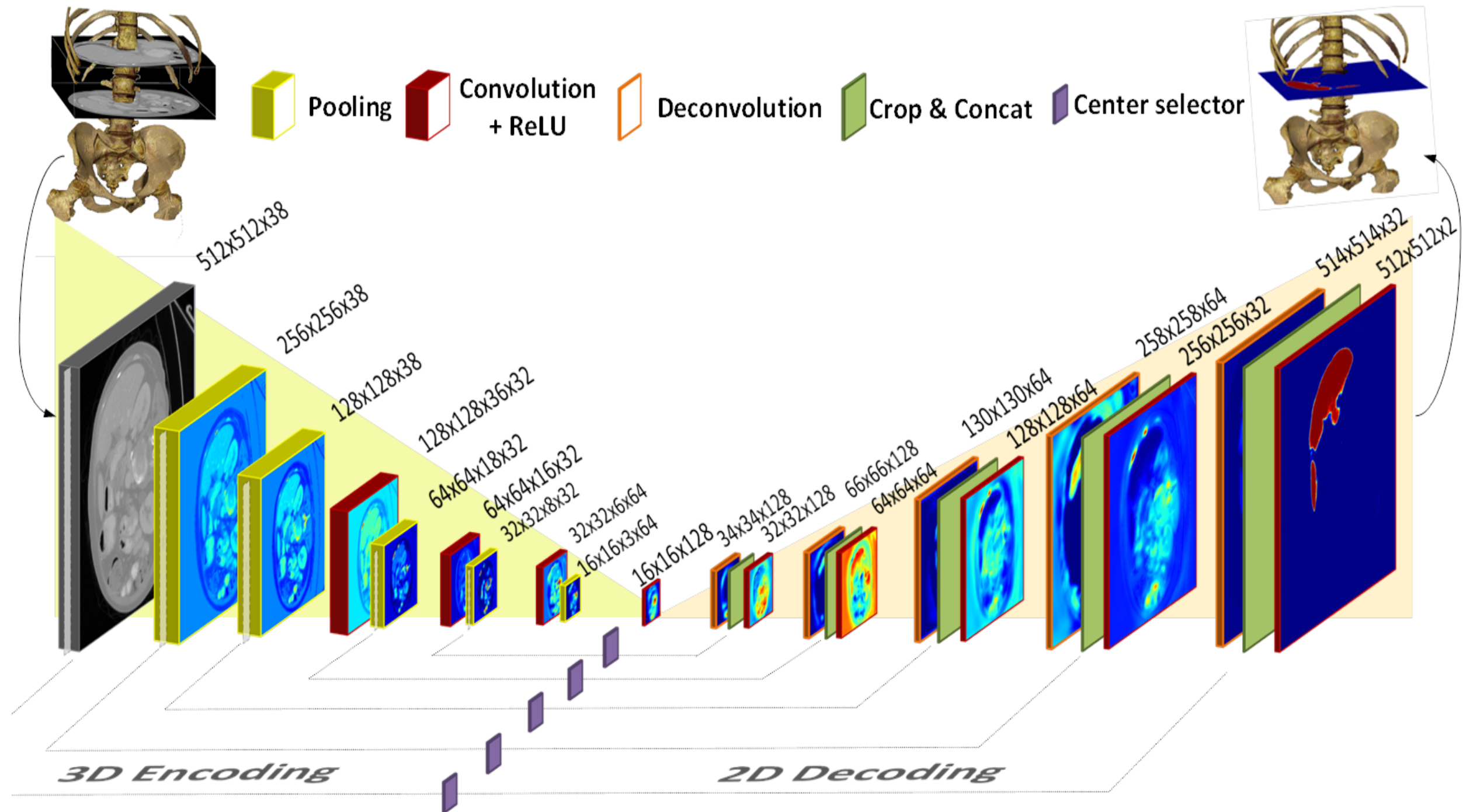
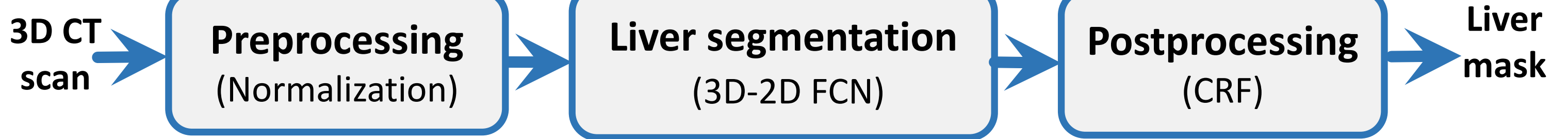
- ❖ **Liver, largest abdominal organ:** Vital for human life but at the risk of trauma, physical injury and cancer.
- ❖ **CT scans:** Gold standard, but a tedious job to analyze slice by slice of a CT scan and prone to human errors.

- ❖ **Automatic Liver Segmentation:** accelerating the process of trauma detection in emergency cases and pre-surgery calculations.
- ❖ **Previous Methods:** Time consuming with high memory usage, so not applicable in clinical settings.

Challenges

- ❖ **Low Quality** of CT images, due to artifacts.(e.g. motion artifacts)
- ❖ Inter-patient and intra-patient extremely **large** variety of **Liver location, size and appearance**
- ❖ Different **contrast phase** (e.g. portal venous) and **field of view**
- ❖ Similar intensity among **adjacent** organs with **vanishing borders**
- ❖ **Undetermined shapes** of liver at beginning and ending slices

Methods



3D-2D FCN Structure

❖ Cost function: Cross Entropy

$$L(x, y) = - \sum_{(x,y) \in \mathbb{Z}^2} \log (p_c(x, y))$$

❖ Pixel weighting

- The closer a pixel is to the boundary, the higher loss is imposed to the network

$$W(x, y) = 1 + w_0 \exp \left(- \frac{d(x, y)}{2\sigma^2} \right)$$

$$E = - \sum_{x,y \in \mathbb{Z}^2} w(x, y) L(x, y)$$

❖ Data augmentation

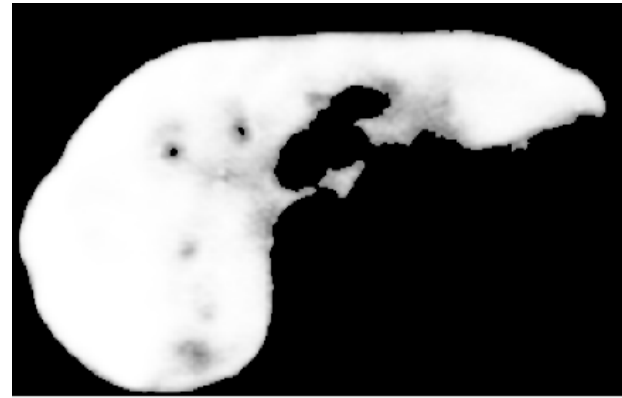
- from -30 to 30 degrees in steps of 10

❖ Dropout layer (last layer of Encoder)

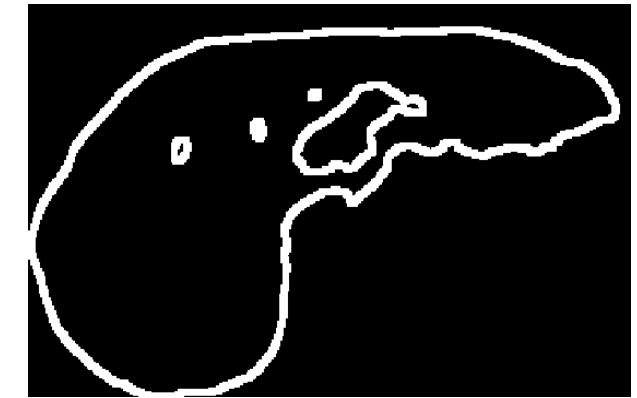
❖ Adam optimizer and Batch Normalization

❖ Early stopping (5-fold cross validation)

CRF PostProcessing



$$\text{Border} = (\text{mask} \oplus SE) - (\text{mask} \ominus SE)$$



Unary = $-\log(p_i)$

Pairwise

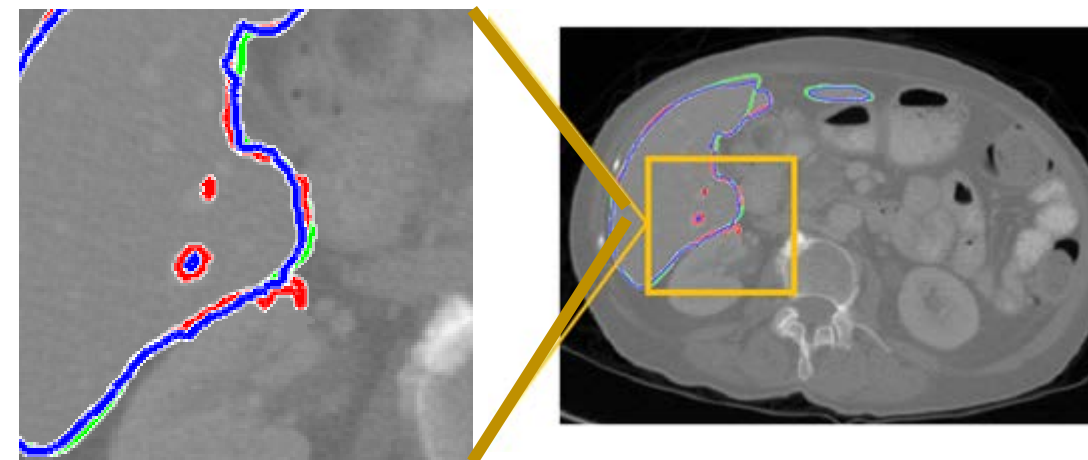
$$E(X) = \sum_i \psi_u(x_i) + \sum_{i,j \in N_i} \varphi_p(x_i, x_j)$$

bilateral

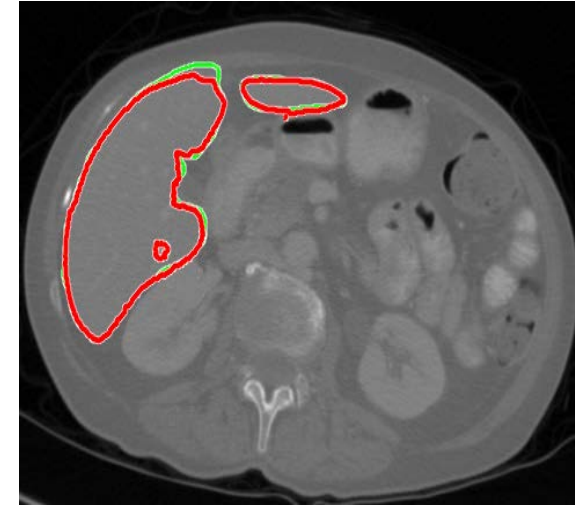
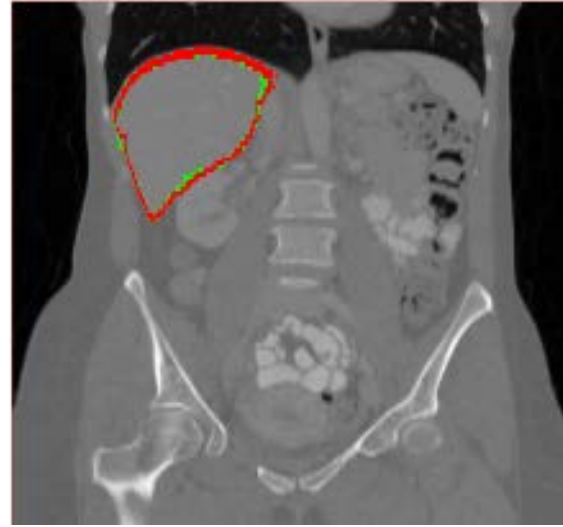
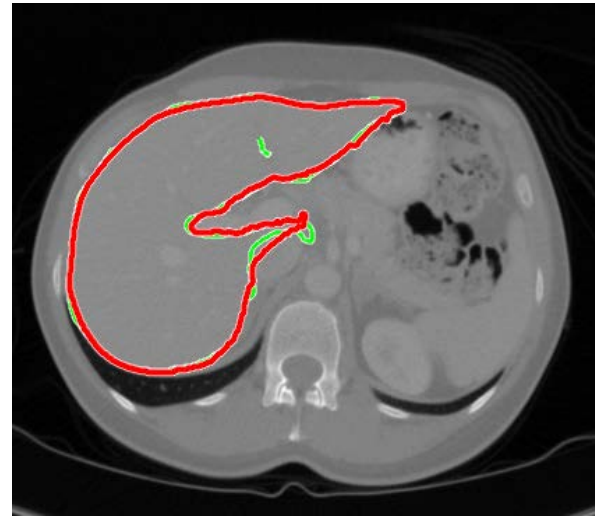
unilateral

$$\varphi_p(x_i, x_j) = \mu(x_i, x_j) \left[w^{(1)} \exp\left(-\frac{|p_i - p_j|^2}{2\theta_\alpha^2} - \frac{|I_i - I_j|^2}{2\theta_\beta^2}\right) + w^{(2)} \exp\left(-\frac{|p_i - p_j|^2}{2\theta_\gamma^2}\right) \right]$$

$$\mu(x_i, x_j) = [x_i \neq x_j]$$



- Ground Truth
- 3D-2D-FCN mask
- CRF enhancement



segmentation algorithms	Dice (%) = $\frac{2TP}{(2TP+FP+FN)}$	Time (second)
Heinrich[4]	92.95	1101
3D-2D-FCN	92.80	42.72
3D-2D-FCN + CRF	93.52	55.59

Table: Results on MICCAI dataset