3D Organ Shape Reconstruction from Topogram Images

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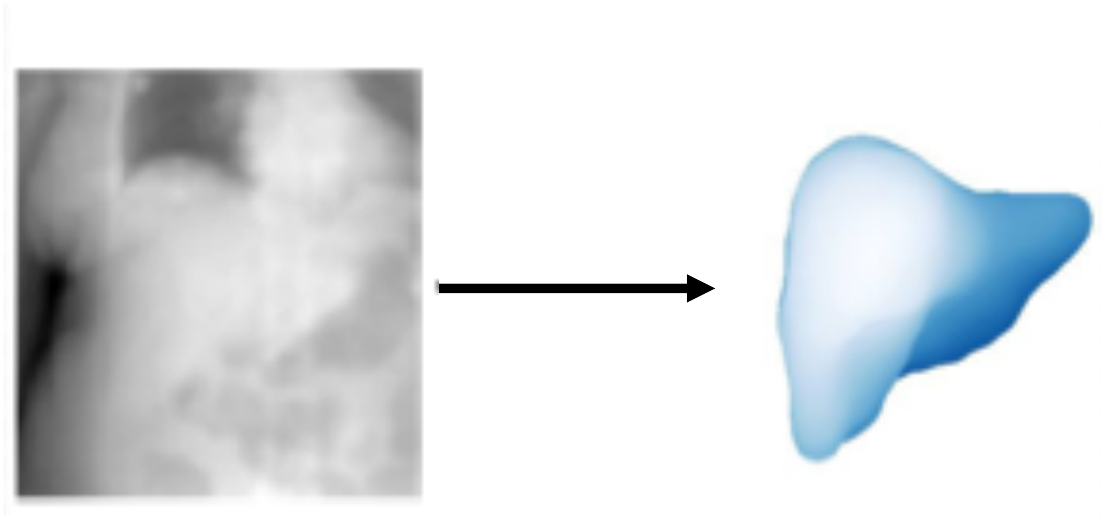
Goal

Automatic delineation and measurement of main organs such as liver is one of the critical steps for assessment of hepatic diseases, planning and postoperative or treatment follow-up. However, addressing this problem typically requires performing computed tomography (CT) scanning and complicated post-processing of the resulting scans using slice-by-slice techniques. In this paper, we show that 3D organ shape can be automatically predicted directly from topogram Images which are easier to acquire and have limited exposure to radiation during acquisition, compared to CT scans. We evaluate our approach on the challenging task of predicting liver shape using a generative model. We also demonstrate that our method can be combined with user annotations, such as a 2D mask, for improved prediction accuracy. We show compelling results on 3D liver shape reconstruction and volume estimation on 2129 CT scans. In particular, we are able to estimate liver volume to 6% accuracy and predict liver shape to 0.90 Dice coefficient.



Training Pipeline

Image + Mask Pipeline

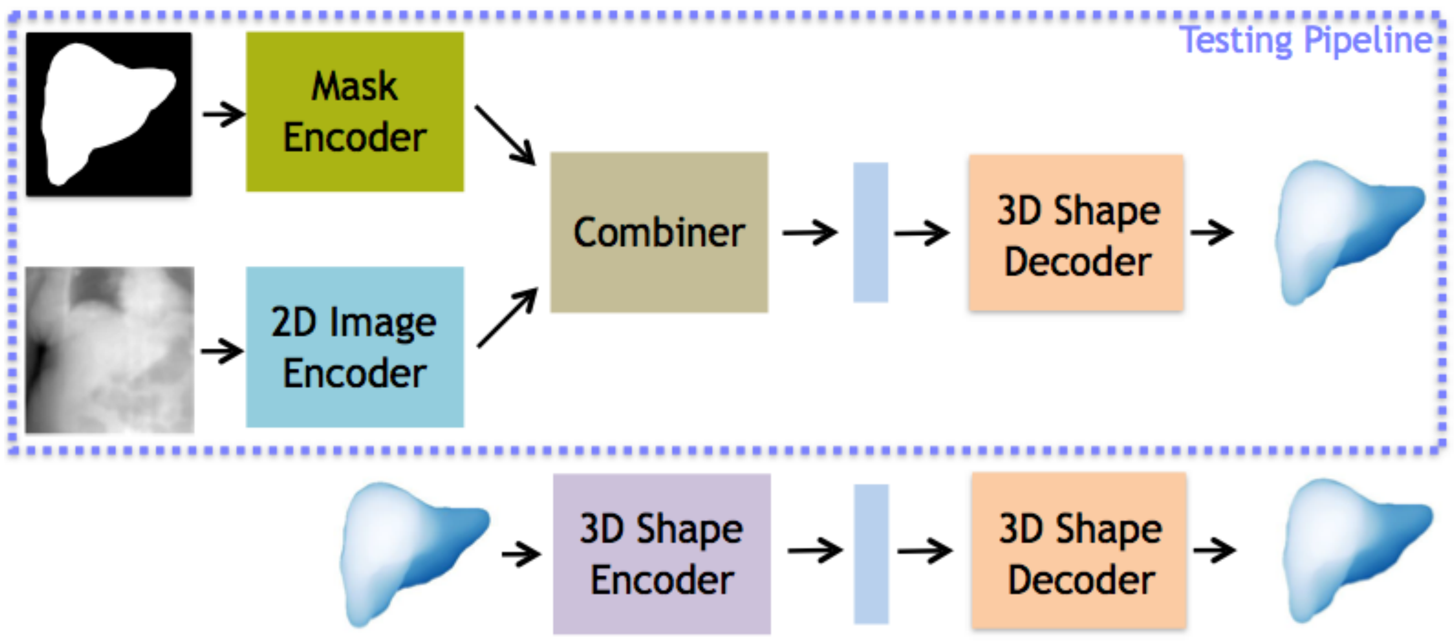
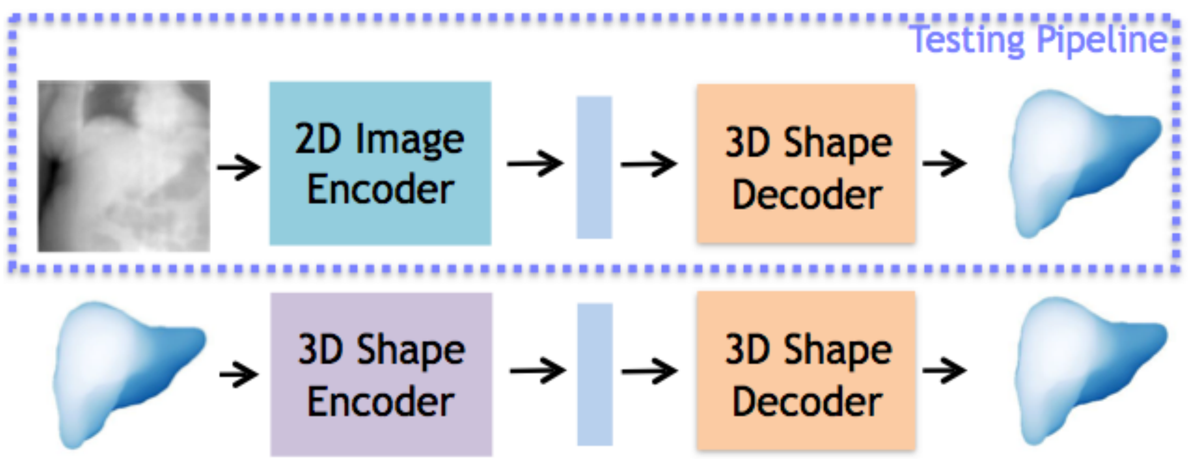


Image Only Pipeline



Loss Optimization

Kullback Leibler divergence

Encoder Output

$$L = \alpha_1 L_{rec}(s, s') + \alpha_2 L_{KL} + \alpha_3 L_{rec}(s, G(\tilde{z})) + \alpha_4 L_{mask}(k, \tilde{k}),$$

Mask Loss

$$L_{mask}(k, \tilde{k}) = -\sum_{n=1}^{N} k_n \log \tilde{k}_n + (1 - k_n)\log(1 - \tilde{k}_n).$$

GT Mask Pred. Mask

BCE Loss

GT Shape Pred. Shape

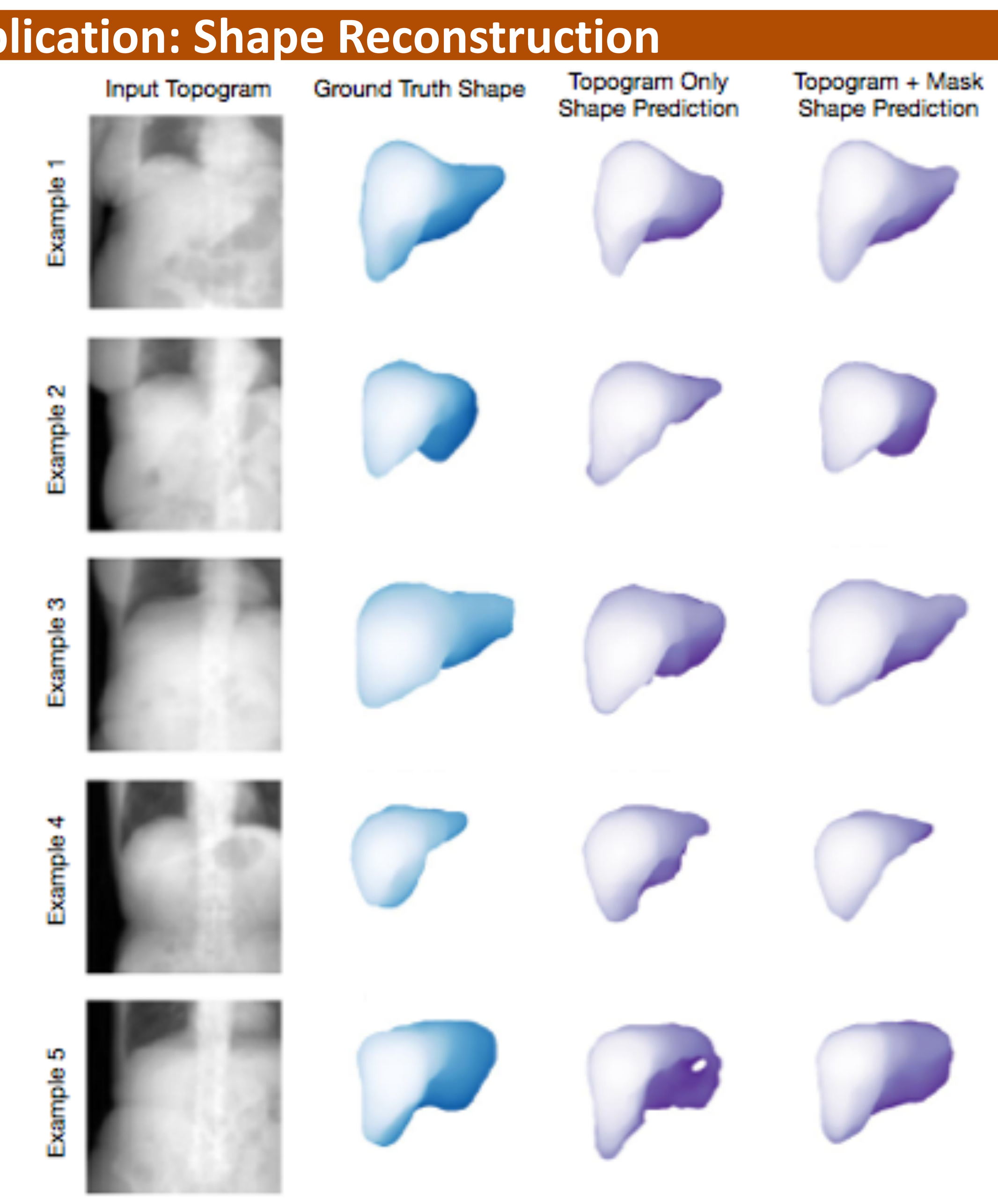
BCE Loss

$$L_{rec}(s, s') = -\frac{1}{N}\sum_{n=1}^{N} s_n \log s'_n + (1 - s_n)\log(1 - s'_n)$$

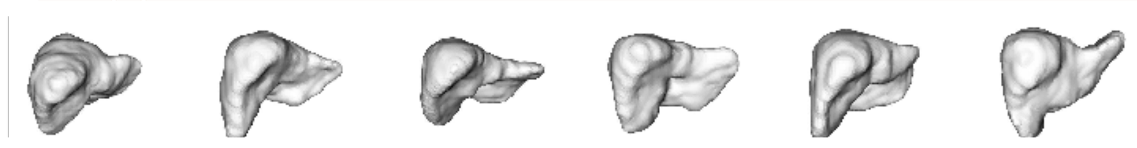
Reconstruction Loss

$\alpha_1, \alpha_2, \alpha_3, \alpha_4$ - Sub-Component weights

Application: Shape Reconstruction



Application: Volume Prediction



Metric	Mask Only	Topogram Only	Topogram + Mask
Volume Error (V_f)	0.34	0.10	**0.06**

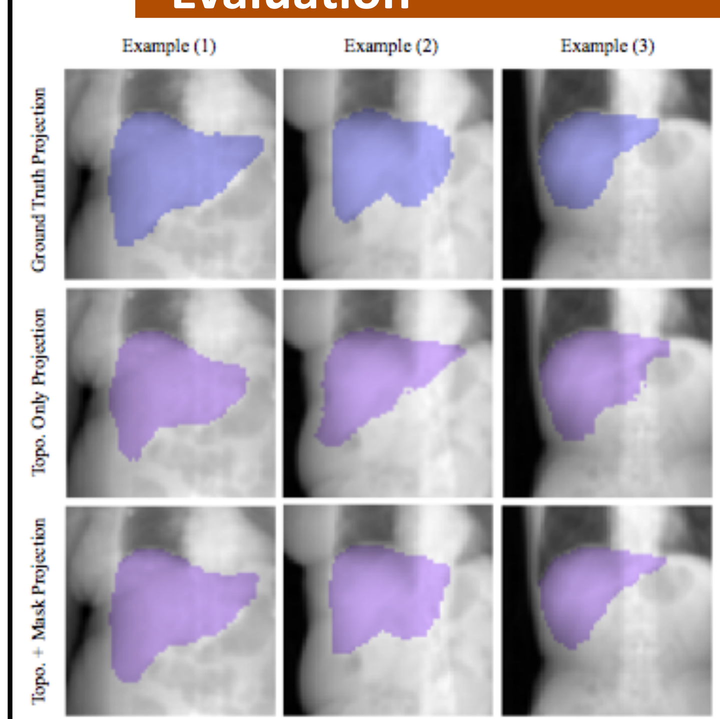
Mean Volume Error evaluation and comparison.

V_{gt} - ground truth volume

V_{pred} - predicted volume

$$V_f = \|V_{pred} - V_{gt}\| / V_{gt}$$

Evaluation



	Volume Prediction	Shape Reconstruction		
	Volume Error (V_f)	IoU	Dice	Hausdorff
Variational Autoencoder (VAE) (without/with mask)	0.10/**0.06**	0.78/**0.82**	0.87/**0.90**	7.10/**5.00**
Adversarial (3D-GAN) [29]	0.21	0.61	0.75	10.50
Performance Difference	109% / 250%	22% / 26%	14% / 17%	48% / 110%

Comparison of the variational auto-encoder (VAE) (with and without mask), and generative adversarial network (GAN) -based approaches on volume prediction and shape reconstruction tasks.

Bibliography

[1] R. Girdhar, D. F. Fouhey, M. Rodriguez, and A. Gupta. Learning a predictable and generative vector representation for objects. In European Conference on Computer Vision pages 484–499. Springer, 2016.
[2] J. Wu, T. Xue, J. J. Lim, Y. Tian, J. B. Tenenbaum, A. Torralba, and W. T. Freeman. Single image 3D interpreter network. In European Conference on Computer Vision, pages 365–382. Springer, 2016.