PATTERN RECOGNITION LAB

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Towards Automatic Abdominal Multi-Organ Segmentation in Dual Energy CT using Cascaded 3D Fully Convolutional Network

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Introduction

- Use dual energy information to improve segmentation accuracy
- First study about automatic multi-organ segmentation on dual energy computed tomography (DECT) images using deep learning
- Based on a cascaded 3D fully convolutional network (FCN) [1]

Material and Methods

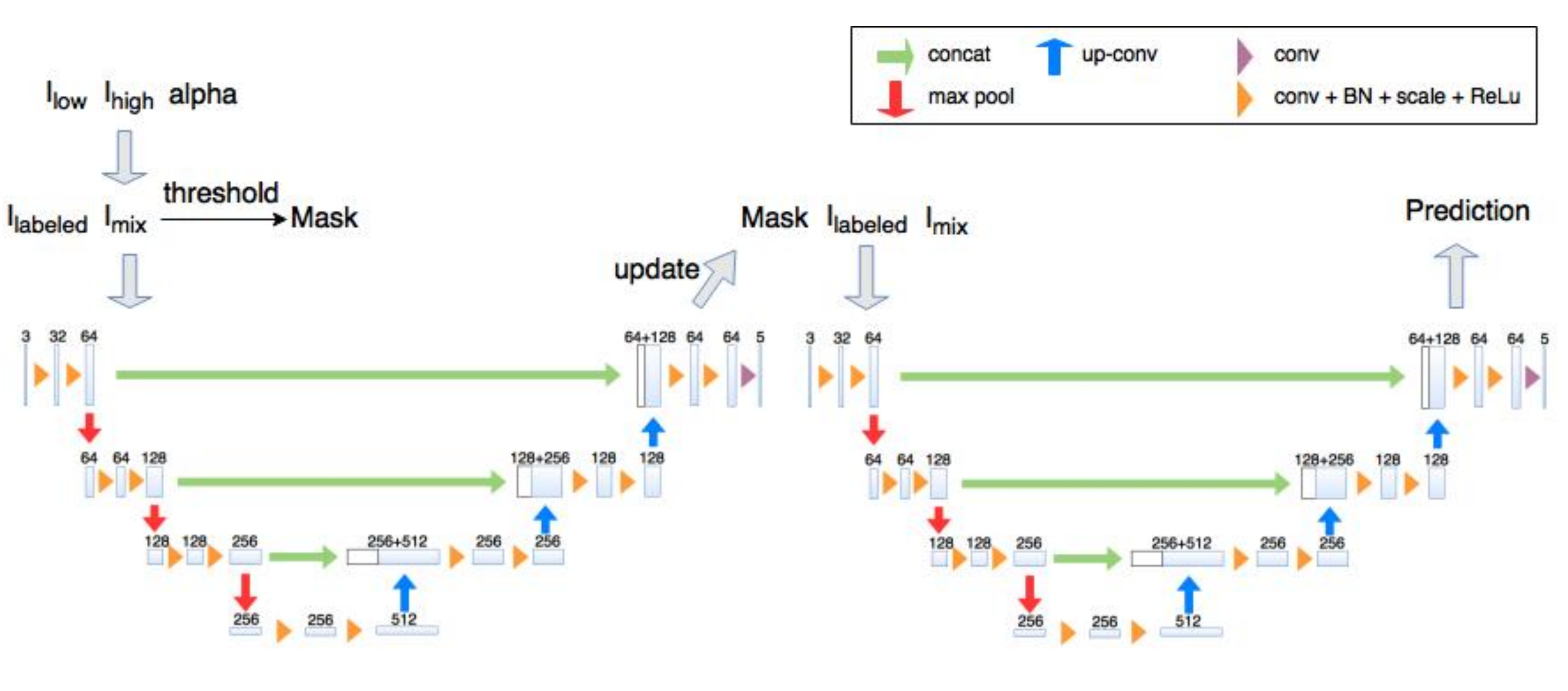

Figure 1: Cascaded network architecture for DECT multi-organ segmentation

- **Image fusion in the preprocessing** based on linear weighting [2]:
  $$I_{mix} = \alpha \cdot I_{low} + (1-\alpha) \cdot I_{high}$$
  -> to merge the images of different energies

- **Binary mask generation** based on thresholding
  -> to undersample the background for the high class imbalance problem

- **Cascaded end-to-end network** (Figure 1):
  - Stage 1: calculation of the region of the interest (ROI)
    -> to further undersample the background and oversample the minor classes
    -> to improve the class weights
    -> ROI is used as mask for the stage 2
  - Stage 2: calculation of the final class probability

- **Voxel-wise class balancing**:
  - Weighted voxel-wise cross-entropy loss using softmax class probabilites p_k :
    $$L = \frac{-1}{N}\sum_{k=i}^{K}\lambda_i \times \left(\sum_{x\forall N_i}\log(\widehat{p_k}(x))\right)$$
  - Weight factor λ_i based on voxel number within ROI N_C [1]:
    $$\lambda_i = \frac{1-{N_i}/{N_C}}{K-1}$$

Results and Discussion

- Experiment setup:
  - 42 clinical torso DECT images
  - Voxel dimensions: [0.6895-0.959, 0.6895-0.959, 0.6] mm
  - 30 for training, 6 for validation, 6 for test, data selected using a **manifold learning-based** technique [3]
  - Data augmentation: rotation, elastic deformation

- Results:
  - **Best results with optimal α** : liver 0.93, spleen 0.92, right kidney 0.91, left kidney 0.89
  - SECT results:
    -> High(α = 0): liver 0.91, spleen 0.88, right kidney 0.84, left kidney 0.85
    -> Low(α = 1): liver 0.92, spleen 0.90, right kidney 0.88, left kidney 0.89

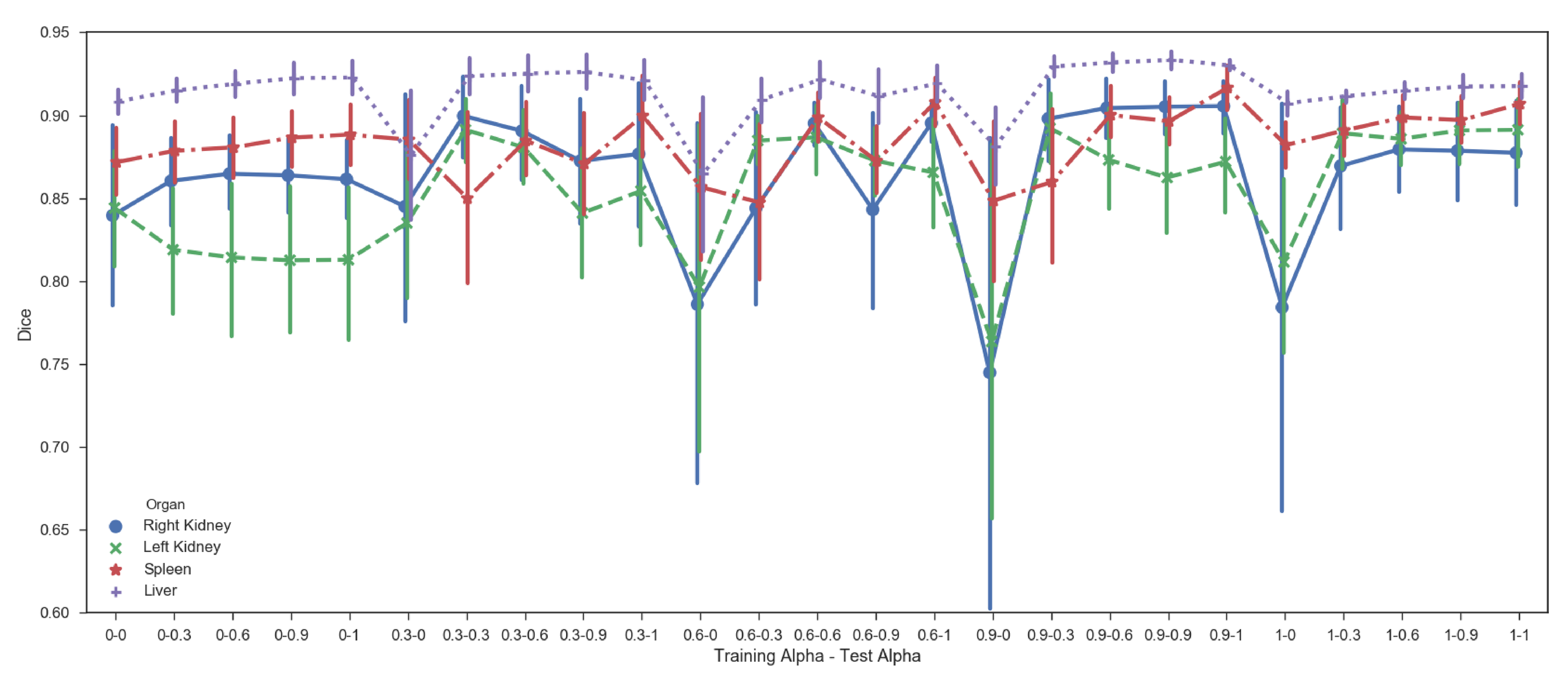

Figure 2: Evaluation with different α

Conclusion

- **DECT accuracy with optimal α is higher than SECT** (α = 0 and α = 1).
- Multi-organ segmentation on DECT using deep learning is promising and robust.
- Data sampling using manifold learning improves the accuracy.
- Image fusion factor α affects the accuracy.
- **The optimal α is organ-different**.

References

1. Roth et al., "Hierarchical 3D fully convolutional networks for multi-organ segmentation," in arXiv preprint arXiv:1704.06382.
2. Krauss et al., *Dual Energy CT in Clinical Practice, chapter Dual Source CT*, Springer Berlin Heidelberg, 2011.
3. Chen et al., "Manifold learning-based data sampling for model training," Procs BVM, 2018, pp. 269–274.

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