Developing Enabling PET-CT Image Analysis Tools for Predicting Response in Radiation Cancer Therapy

Xiaodong Wu[1,2] Yusung Kim[2] John Buatti[2]

[1] Department of Electrical and Computer Engineering
[2] Department of Radiation Oncology
University of Iowa
IOWA, USA

THE IOWA INSTITUTE FOR BIOMEDICAL IMAGING

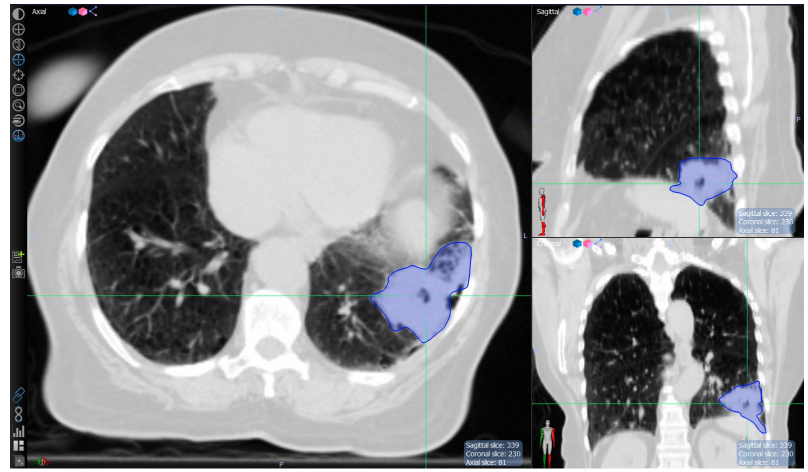
THE UNIVERSITY OF IOWA

Outline

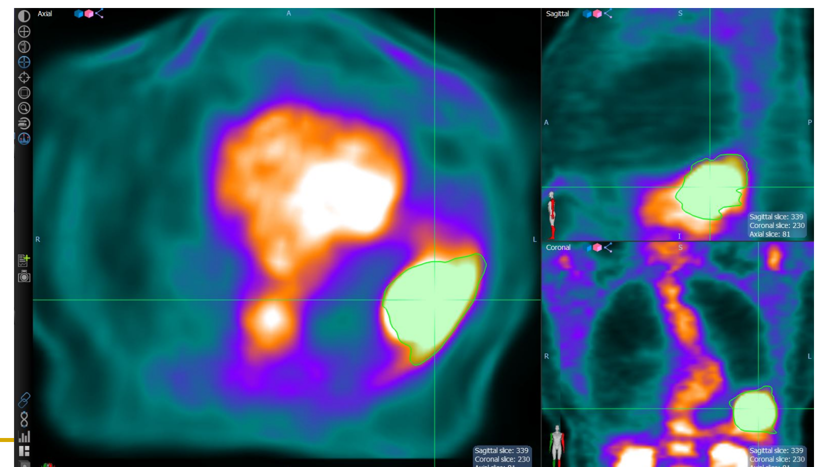
- Overview of the project
- PET-CT co-segmentation
- Next step

Motivation

PET-CT has revolutionized modern cancer imaging



- Diagnosis
- Tumor staging
- Therapeutic response prediction
- Treatment planning
- Prognosis assessment



Major Goal

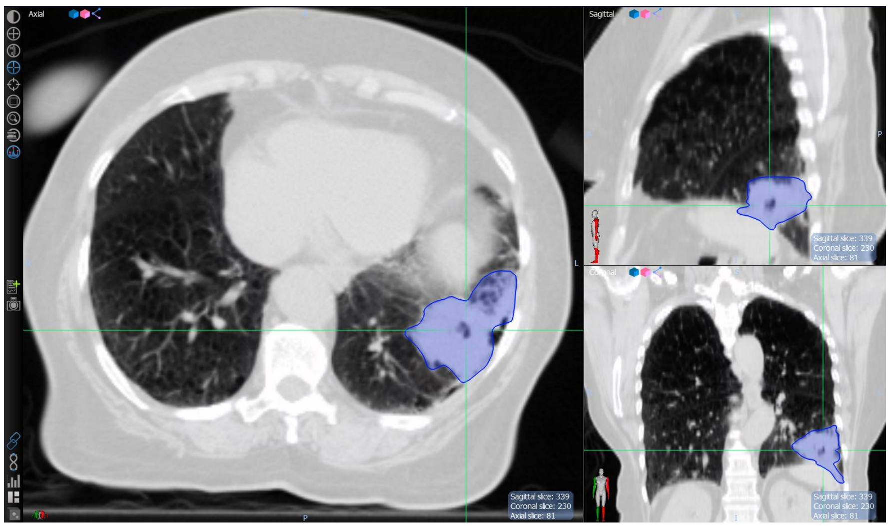
- To develop novel algorithms, methods, and general tools
  - Automated and objective analysis of PET-CT images
  - To facilitate the use of PET-CT imaging in the response prediction for radiation therapy

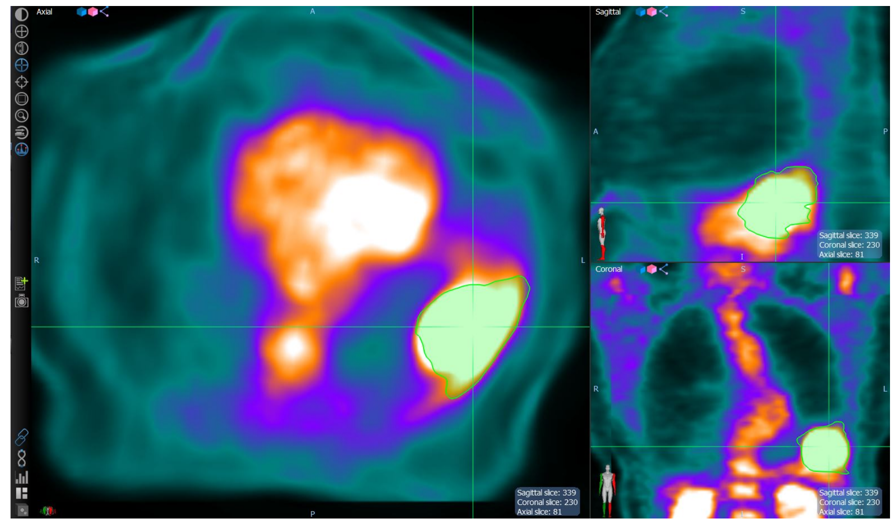
Specific Aims

- Develop and validate a graph-based optimal co-segmentation method for tumor delineation from PET-CT, while admitting the inherit uncertainties in imaging and registration.
- Develop and evaluate an efficient method for therapeutic response prediction using automatically learned hierarchical features directly from PET-CT scans.

Innovation

- Tumor co-segmentation in PET-CT
  - Tumor contours on PET and on CT are different





  - PET and CT may not well aligned
  - Use different imaging mechanisms

Innovation

rent

Multimodality imaging with CT, MR and FDG-PET for radiotherapy target volume delineation in oropharyngeal squamous cell carcinoma

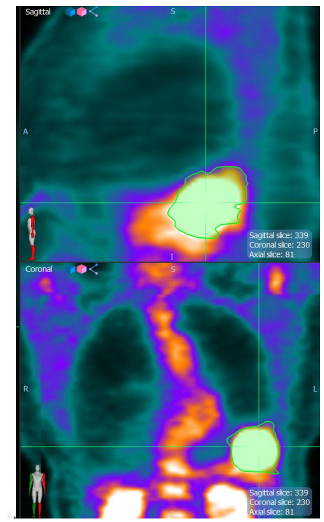
David Bird[1], Andrew F. Scarsbrook[2,3], Jonathan Sykes[1], Satiavani Ramasamy[4], Manil Subesinghe[2,3], Brendan Carey[3], Daniel J. Wilson[5], Neil Roberts[6], Gary McDermott[5], Ebru Karakaya[4], Evrim Bayman[4], Mehmet Sen[4], Richard Speight[1] and Robin J.D. Prestwich[4*]

Abstract

Background: This study aimed to quantify the variation in oropharyngeal squamous cell carcinoma gross tumour volume (GTV) delineation between CT, MR and FDG PET-CT imaging.

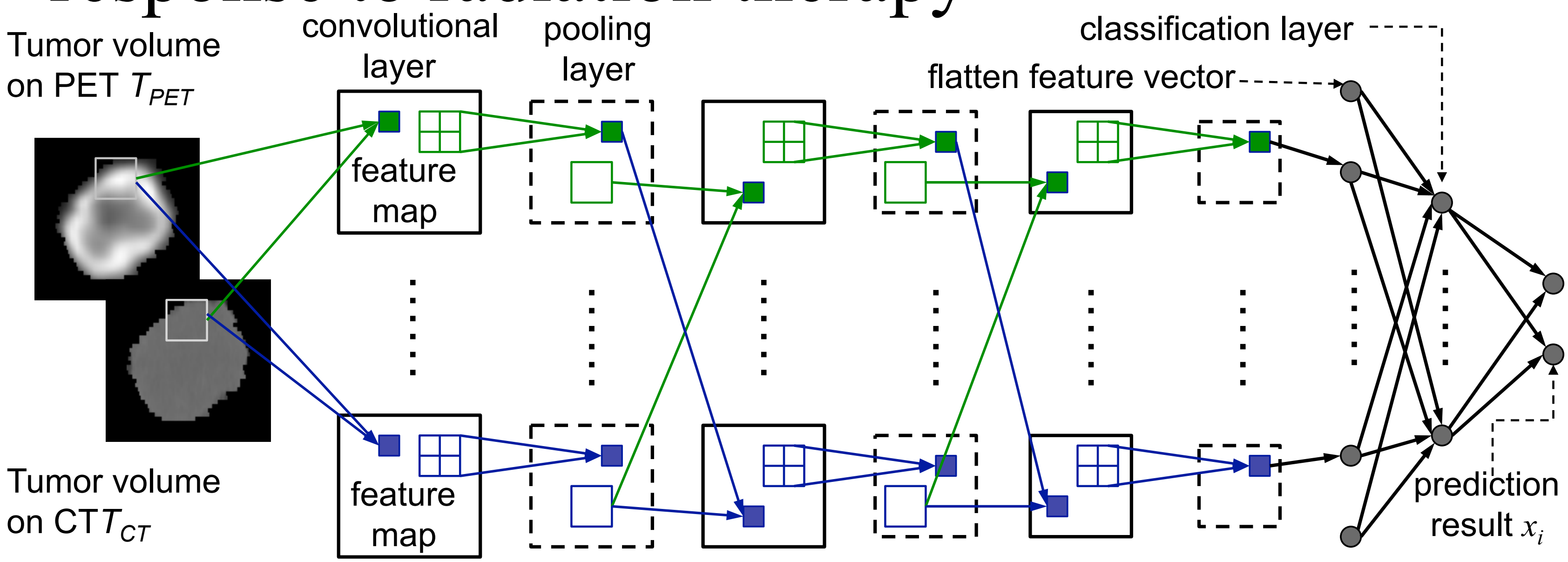
Methods: A prospective, single centre, pilot study was undertaken where 11 patients with locally advanced oropharyngeal cancers (2 tonsil, 9 base of tongue primaries) underwent pre-treatment, contrast enhanced, FDG PET-CT and MR imaging, all performed in a radiotherapy treatment mask. CT, MR and CT-MR GTVs were contoured by 5 clinicians

Conclusions: The use of different imaging modalities produced significantly different GTVs, with no single imaging technique encompassing all potential GTV regions. The use of MR reduced inter-observer variability. These data suggest delineation based on multimodality imaging has the potential to improve accuracy of GTV definition.



Innovation

- Deep learning for predicting therapeutic response to radiation therapy



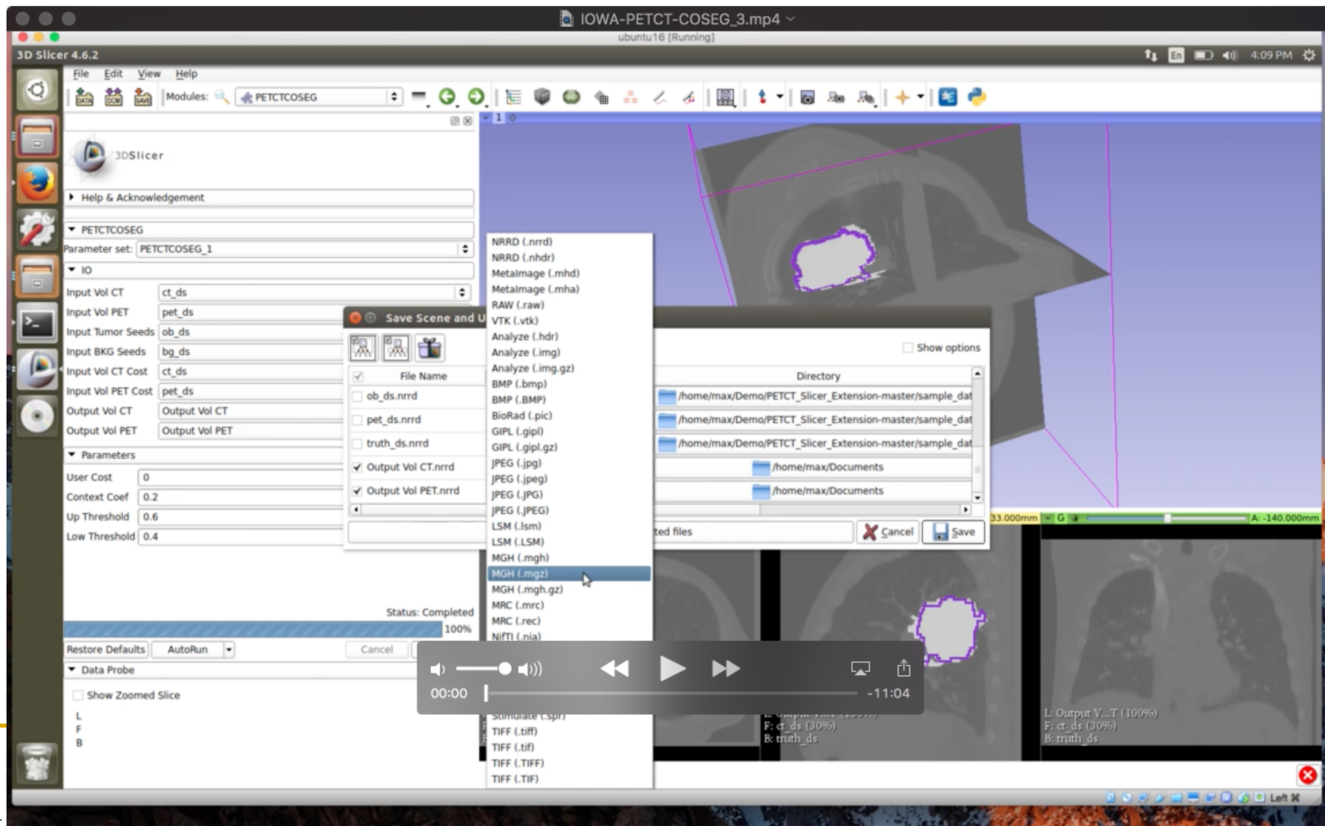
  - Data driving
  - Automated extract highly expressive imaging features for response prediction

THE UNIVERSITY OF IOWA

THE IOWA INSTITUTE FOR BIOMEDICAL IMAGING

Project Progress

- Aim 1 – PET-CT co-segmentation
  - Software development
    - Implemented as a 3D-Slicer extension module with GUI



Project Progress

- Aim 1 – PET-CT co-segmentation
  - Code is publically available
    - GitHub - https://github.com/IOWA-PETCT-COSEG/PETCT_Slicer_Extension
  - User instruction video
    - YouTube - https://youtu.be/sRlCCZpK3oQ
    - GitHub - https://github.com/IOWA-PETCT-COSEG/PETCT-COSEG-Video
  - Improving cost function design

Project Progress

- Aim 2 – Prediction of therapeutic response
  - Data collection
    - 105 lung cancer cases with Stereotactic Body Radiation Therapy (SBRT)
    - Pre-therapy PET-CT
    - Post-therapy CT
  - Generate ground truth for training CNN

TABLE 1: Evaluation of Target and Nontarget Lesions by Response Evaluation Criteria in Solid Tumors (RECIST), Version 1.0

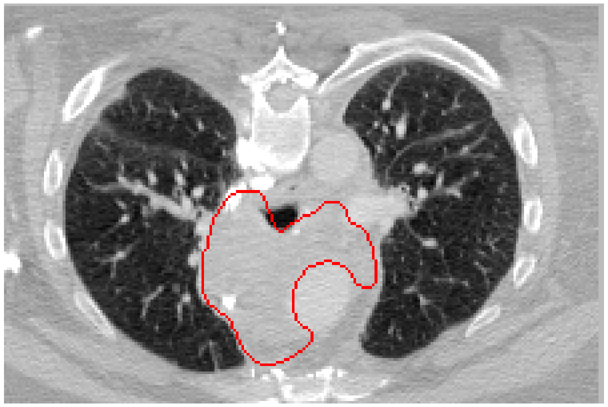
Response Assessment	RECIST Guideline, Version 1.0
Evaluation of target lesions	
CR complete response	Disappearance of all target lesions
PR partial response	≥ 30% decrease in the sum of the longest diameters of target lesions compared with baseline
PD progressive disease	≥ 20% increase in the sum of the longest diameter of target lesions compared with the smallest-sum longest diameter recorded or the appearance of one or more new lesions
SD stable disease	Neither PR or PD

Outline

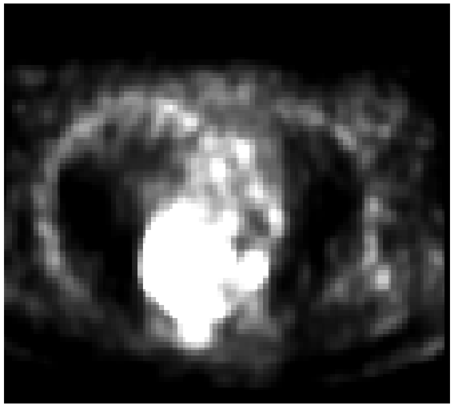
- Overview of the project
- PET-CT co-segmentation
- Next step

Rational for Co-Segmentation

- Different modalities provide different information



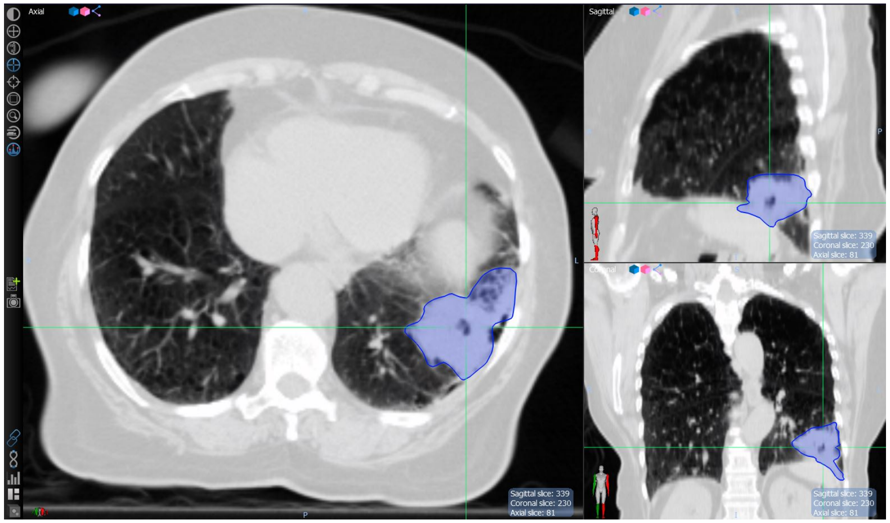
One slice of CT image for the treatment planning of lung tumor

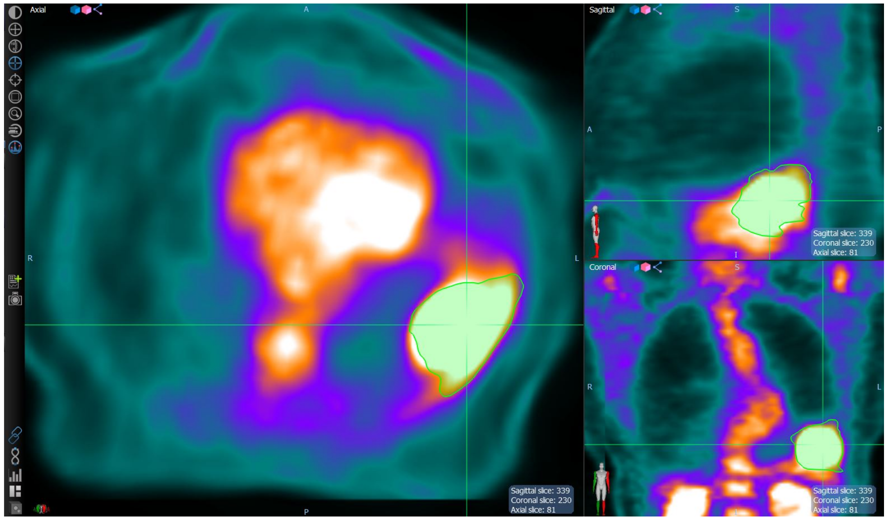


Corresponding PET image

Rational for Co-Segmentation

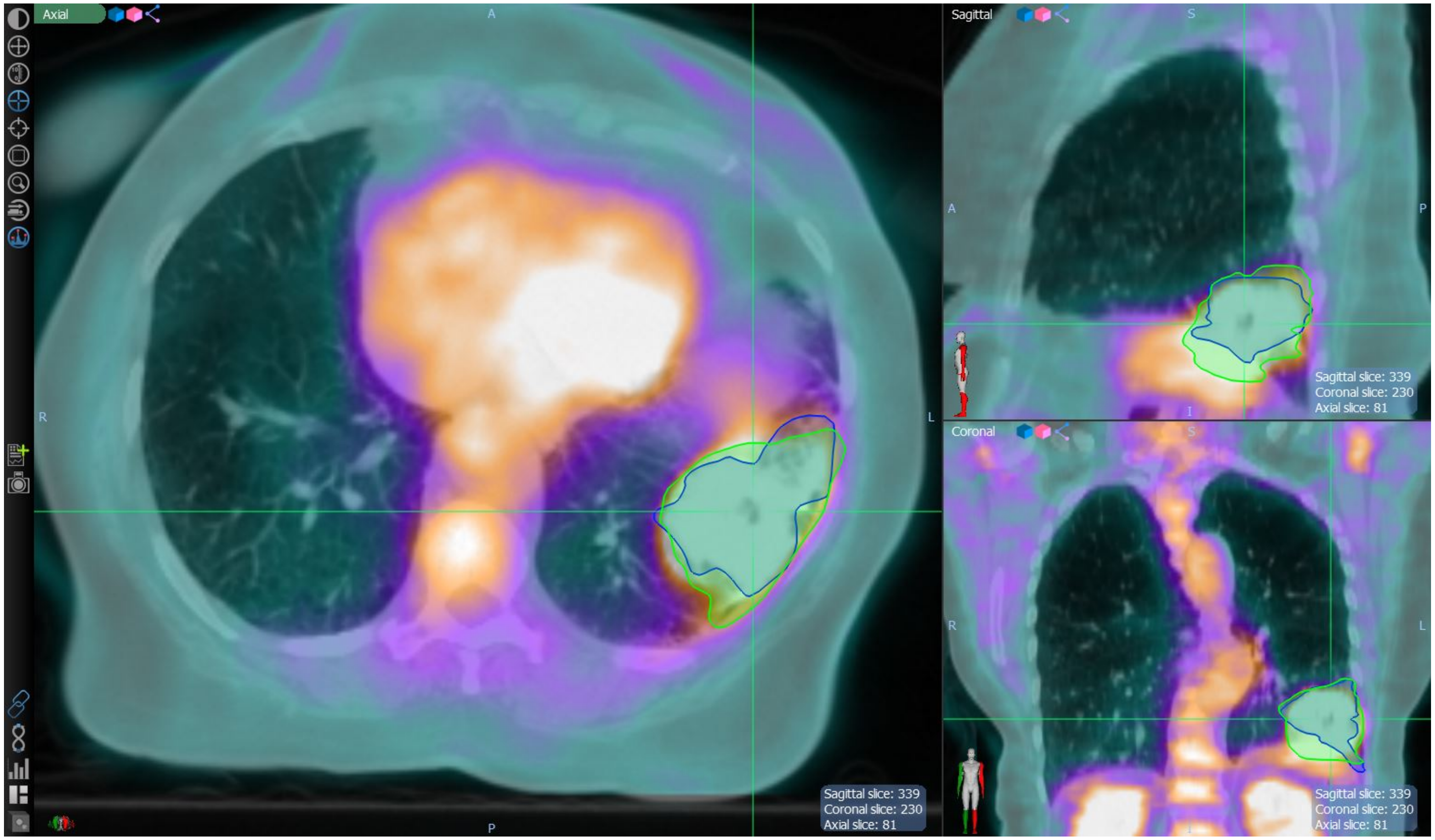
- Tumor contour difference in PET and CT





Rational for Co-Segmentation

- Tumor contour difference in PET and CT

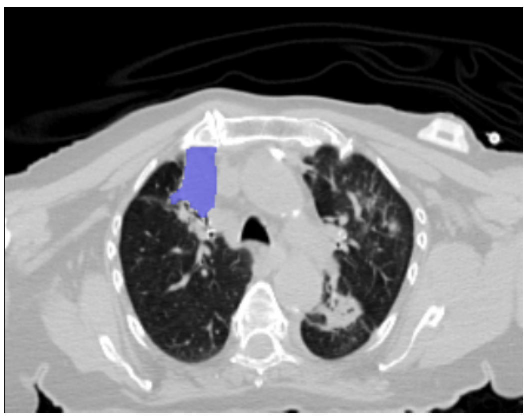


THE UNIVERSITY OF IOWA

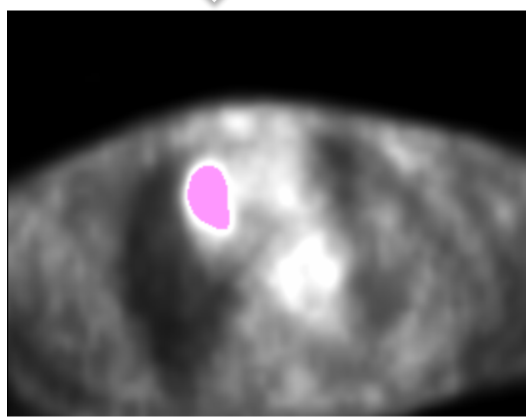
THE IOWA INSTITUTE FOR BIOMEDICAL IMAGING

Energy Function

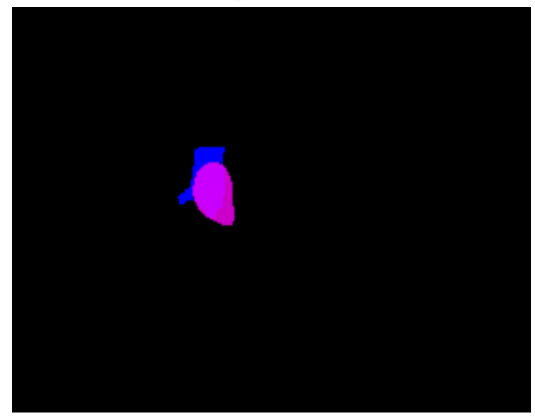
$$E(l) = E_{CT}(l_v) + E_{PET}(l_{v'}) + E_{context}(l_v, l_{v'})$$



Segmentation in CT image



Segmentation in PET image

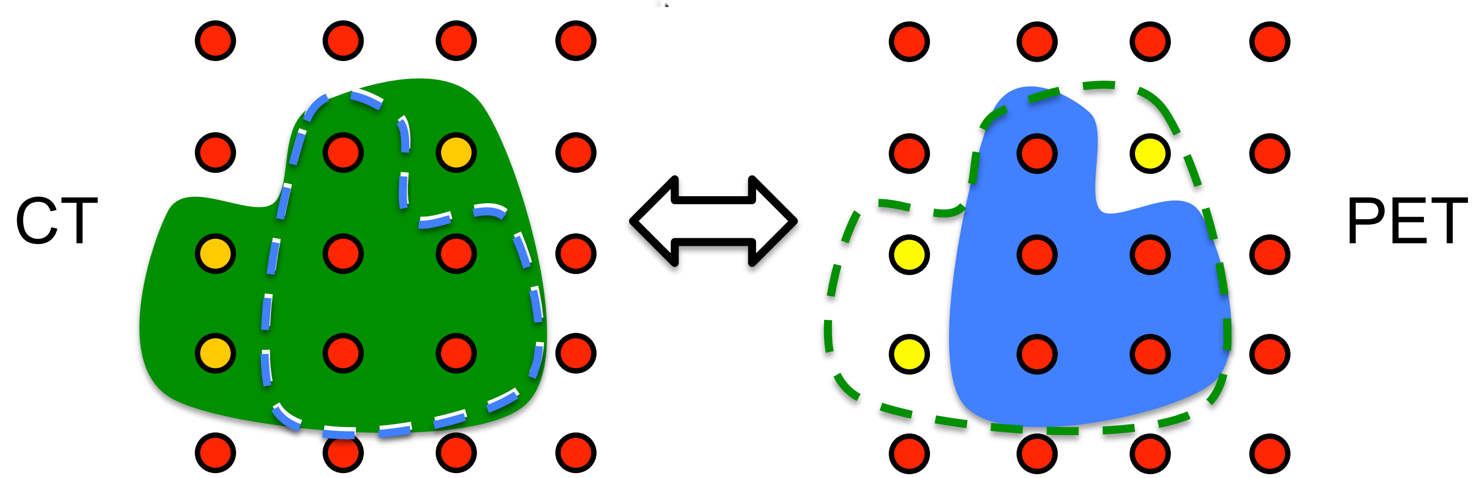


Context term penalizing segmentation differences between CT-PET images

Energy Function

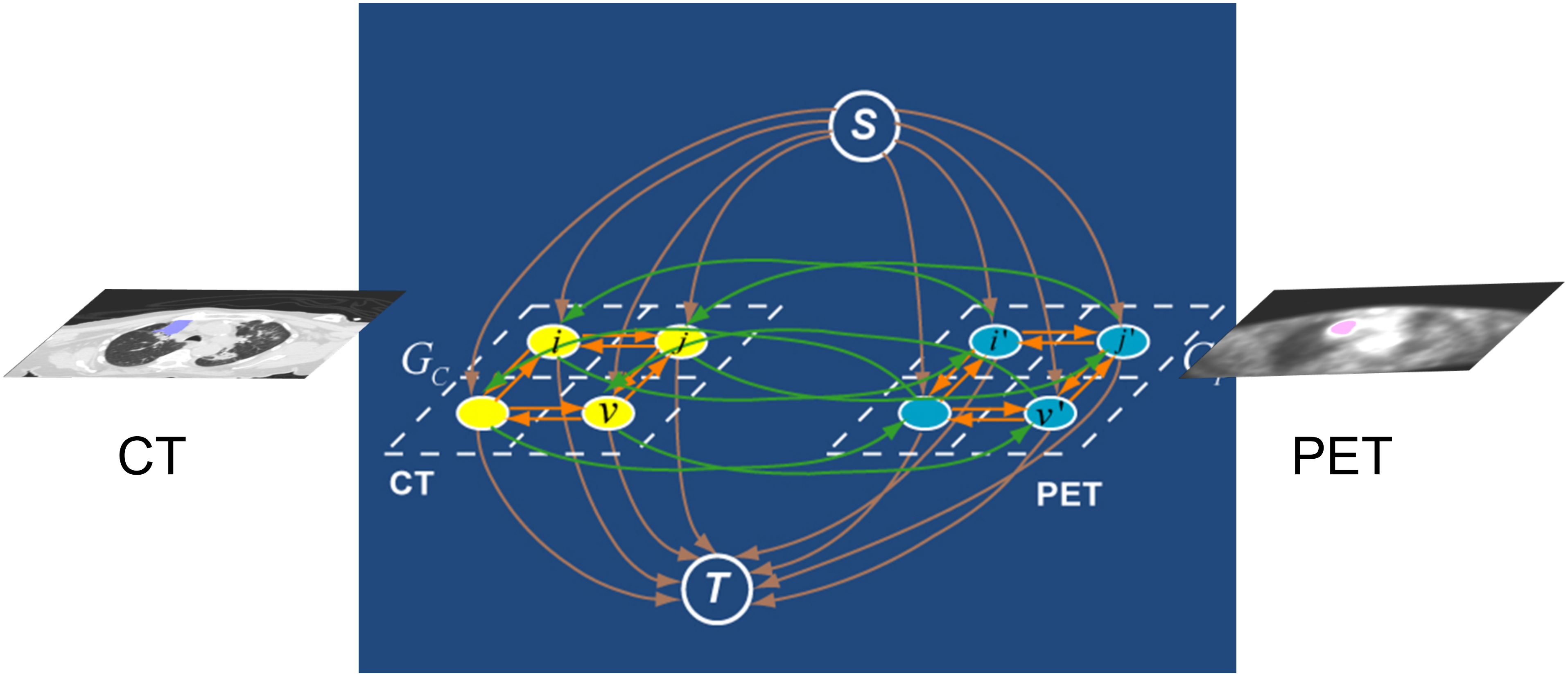
- Incorporation of context constraints

$$E_{\text{context}}(l) = \sum_{(v,v')} W_{vv'}(l_v, l_{v'}). \quad W_{vv'}(l_v, l_{v'}) = \begin{cases} C_{vv'}, & \text{if } l_v \neq l_{v'} \\ 0, & \text{if } l_v = l_{v'} \end{cases}$$



For voxel pairs without consistent labeling in PET and CT (yellow), a penalty $C_{vv'}$ is given

Graph Optimization



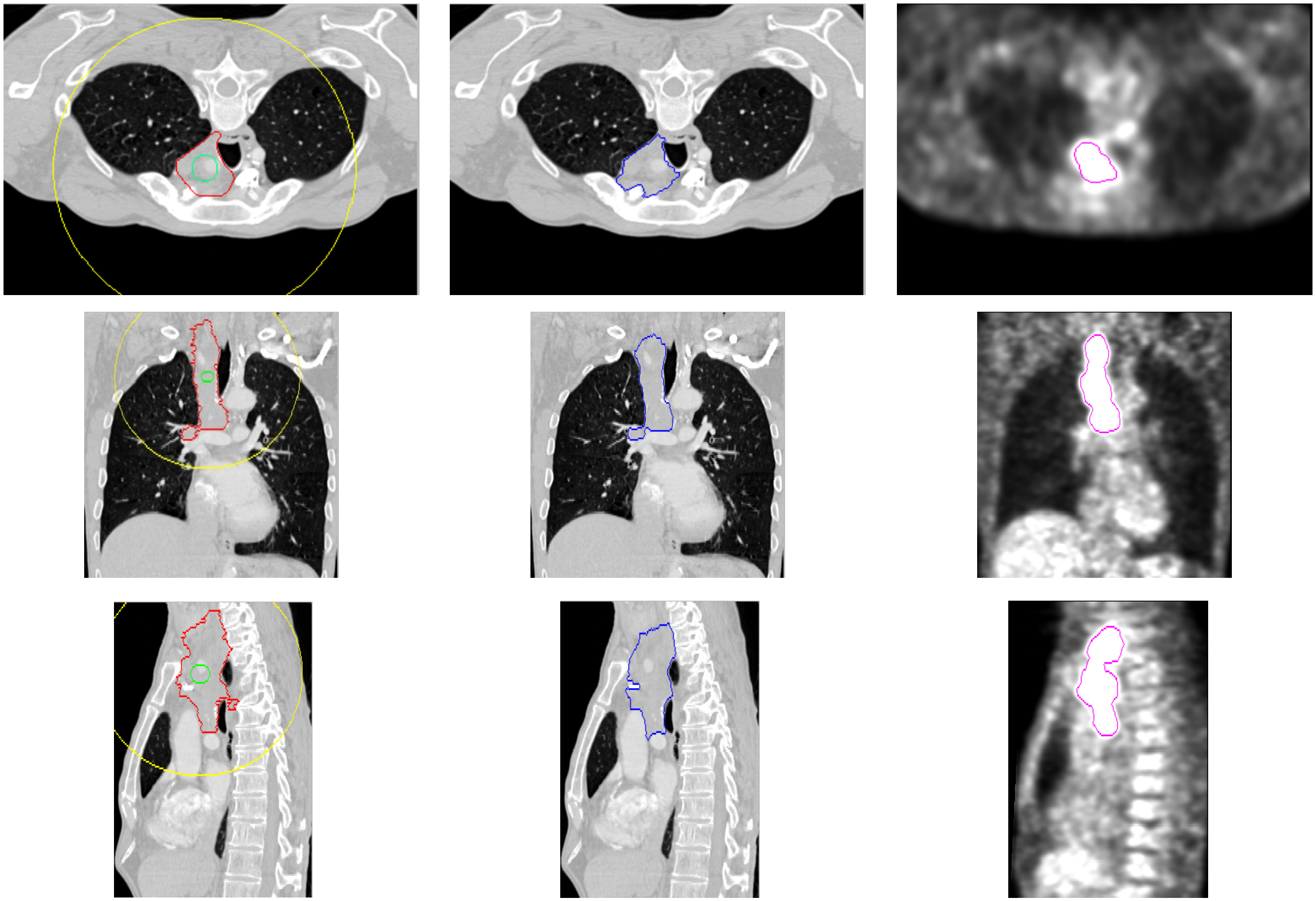
Experiments & Results

- 54 sets of 3-D FDG-PET-CT images were obtained from different patients.
- Image size:
  - CT: 512x512 voxels/slice, voxel: 0.98x0.98x2.0 – 1.37x1.37x2.00 mm^3
  - PET: 128x128 to 168x168 voxels/slice, voxel: 3.39x3.39x2.02 to 4.07x4.07x4.00 mm^3
- 10 datasets used for training and tested on the remaining 44 datasets

Experiments & Results

Methods	Modalities	Mean Dices	Standard Deviations	P-values
Pervious	CT-only	0.495	0.208	
	PET-only	0.582	0.134	
	Coseg.	0.768	0.114	
Improved	CT-only	0.744	0.101	1e-10
	PET-only	0.757	0.077	1e-13
	Coseg.	**0.802**	0.069	0.005

Illustrative Results

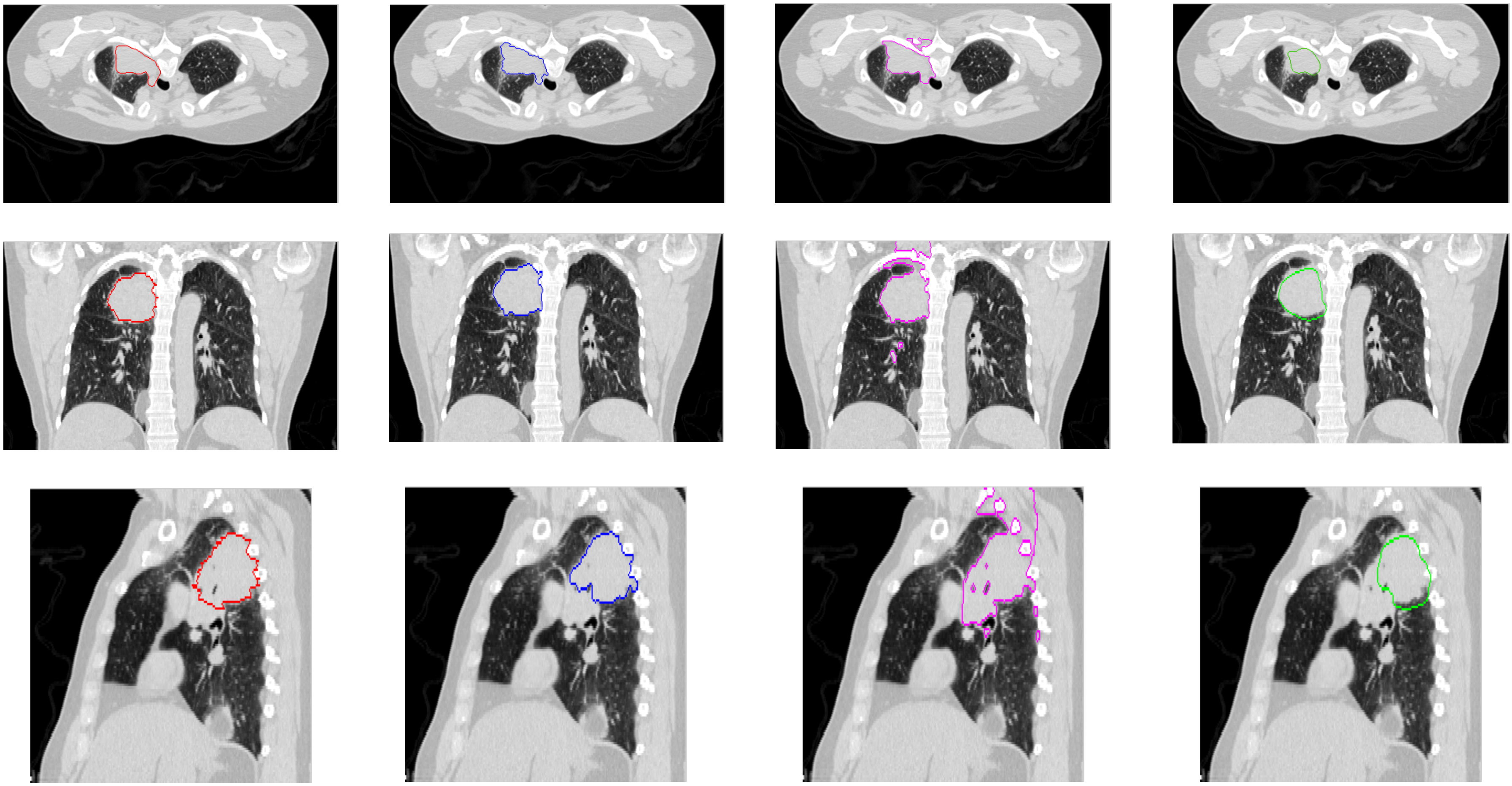


Manual Results Segmentation on CT Segmentation on PET

THE UNIVERSITY OF IOWA

THE IOWA INSTITUTE FOR BIOMEDICAL IMAGING

Comparative Results



Manual Segmentation	Co-segmentation with context constraints	Graph-cut solely using CT	Graph-cut solely using PET

Outline

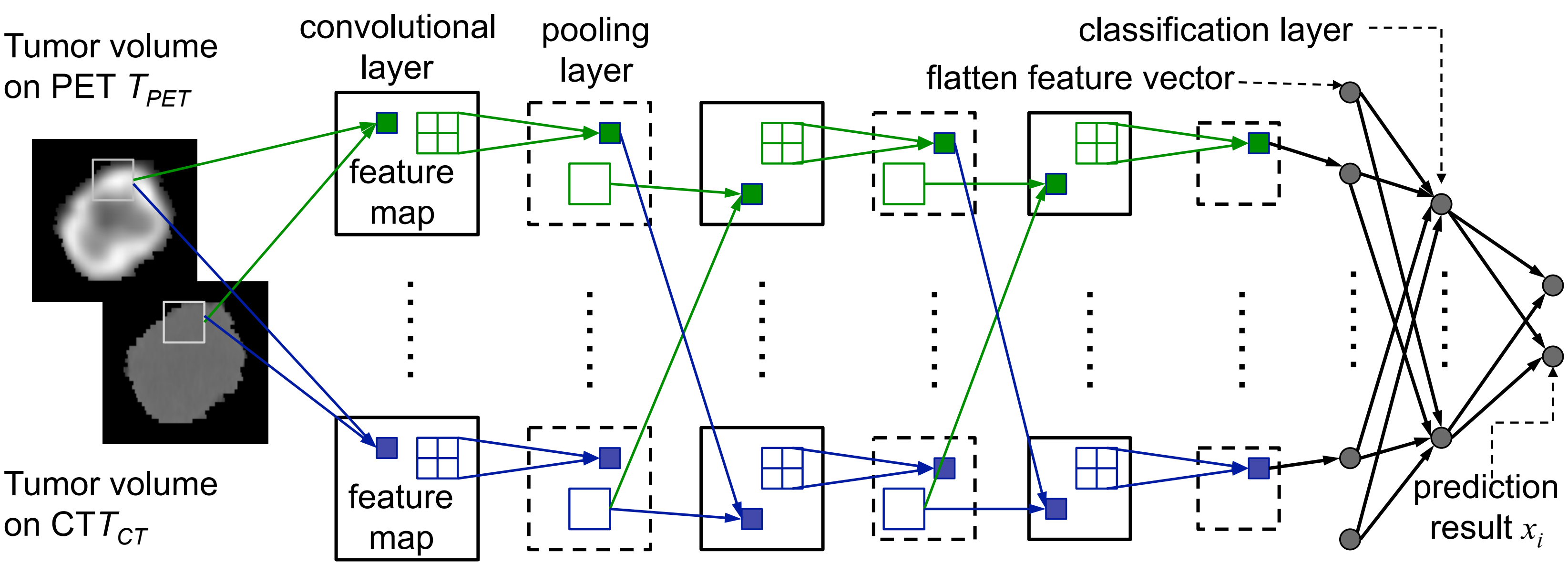
- Overview of the project
- PET-CT co-segmentation
- Next step

Aim 1 – Co-Segmentation

- Pack the improvement on cost function to our 3D-Slicer extension module
- Further validate the method with both PET and CT tumor contours of 50 PET-CT images of SBRT cases.
- Integrate our co-segmentation model into the deep learning framework.

Aim 2 – Response Prediction

- Further refine our deep prediction network.



- Implementation and valuation
- Make it publically available

Thank You!
Questions?

Acknowledgments: This research is under support in part by NCI R21CA209874.

THE UNIVERSITY OF IOWA

THE IOWA INSTITUTE FOR BIOMEDICAL IMAGING