Physics-Based Machine Learning for Image Segmentation

Jonas Actor

Rice University

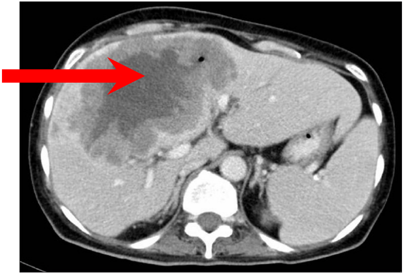
26 February 2018

Dr. Béatrice Rivière
Rice University

Dr. David Fuentes
MD Anderson Cancer Center

Contact: jonasactor@rice.edu

Motivation: Hepatocellular Carcinoma (HCC)



Segmented liver with HCC-type cancer (arrow)

- $\sim$ 1 million cases and deaths annually
- No curative treatments for roughly 80% of patients
- Need for reliable models of patient response $\rightarrow$ segmentation

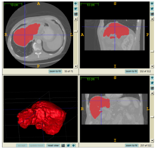
Image: Dey et al., Indian Journal of Cancer, 2011

Step 1: Segmentation via Unrolling

CT data

Neural Network (NN)

Segmentation



PDE Image Analysis

Left: Olson, Naval Medical Center Portsmouth, 2010
Right: Fuentes, MD Anderson, 2018

Step 1: Segmentation via Unrolling

Unrolling: transforms regularized minimization problem into NN

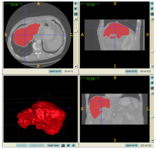
CT data

Neural Network (NN)

Unrolling

PDE Image Analysis

Segmentation

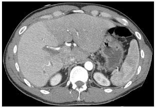


- PDE informs NN architecture
- Training NN solves a PDE minimization problem

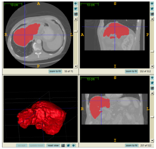
Left: Olson, Naval Medical Center Portsmouth, 2010
Right: Fuentes, MD Anderson, 2018

Step 2: Making Clinical Treatment Decisions

CT scan



Unrolling



Segmentation

Data Driven Model: Predict Patient Response

Tumor Data:

- number of tumors
- location
- size

Liver Data:

- surrounding tissue
- blood flow
- porosity

Translational Research

Use segmentation as a **tool for clinical decision support**
in **Healthcare and Clinical Informatics**

Research Goals:

- Segment CT data via unrolling, combining NN + PDEs
- Evaluate performance using ~200 labeled datasets from MD Anderson and elsewhere
- Perform machine learning on patient data obtained from segmentation to buld a comprehensive data-driven treatment assessment model

Interdisciplinary Mentoring Plan

Dr. Rivière (primary)

- Numerical solution of PDE's
- Numerical analysis
- Mathematical biology
- Resources from applied mathematics community

Dr. Fuentes (secondary)

- Medical image analysis
- Mathematical models for decision support
- Access to patients, clinic, data
- Resources from medical imaging community

My responsibilities:

- Meet with both mentors weekly
- Communicate research across medical imaging, clinical, applied mathematics, and machine learning communities

Practicum and Curriculum

Research Practicum:

- Enroll in CAAM 800 Independent Research
- Meet with surgeons and oncologists at MD Anderson
- Report on how segmentation data is used in clinical treatment decision support

Required	COMP 543	Graduate Tools and Models	F 18
	HI 5310	Foundations of Health Information Sciences I	S 19
Electives	STAT 581	Mathematical Probability	F 17
	BIOE 591	Fundamentals of Medical Imaging	F 18
	GS-SB-405	Computer-Aided Discovery Methods	S 20
Workshop		GCC Rigor and Reproducibility	F 18
RCR	UNIV 594	Responsible Conduct in Research	F 18
Keck Seminar	BIOS 592	Topics in Quantitative Biology	S 20

Physics-Based Machine Learning for Image Segmentation

Jonas Actor

Rice University

26 February 2018

Dr. Béatrice Rivière
Rice University

Dr. David Fuentes
MD Anderson Cancer Center

Contact: jonasactor@rice.edu

RICE

Timeline

Spring 2018	Complete Master's Thesis
Summer 2018	Begin application to clinical data
Fall 2018	Begin theoretical analysis of unrolling
Spring 2019	Complete theoretical analysis of unrolling Implement unrolling segmentation methods Publication of theoretical analysis
Summer 2020	Develop efficient computational schemes
Fall 2020	PhD Proposal
Spring 2021	PhD Defense

Communication of Research

Some Conferences:

- AMIA Annual Symposium, November 2019
- SIAM Imaging Sciences, June 2020
- IEEE Conference on Computer Vision, Summer 2019
- SPIE Medical Imaging, February 2019, 2020

Some Journals:

- JAMIA
- IEEE Medical Imaging
- SIIMS
- NIPS

Unrolling

- First used for sparse compressive sensing
- Recasts iterative minimization as neural network (NN)

Unrolling: Compressive Sensing

$$\min_{z} \|Dz - x\|_2^2 + \lambda \|z\|_1$$

- x: original signal
- z: reconstructed **sparse** signal
- D: Dictionary (maps sparse to full signal)

Unrolling: Compressive Sensing

$$\min_z \|Dz - x\|_2^2 + \lambda \|z\|_1$$

Keeps our reconstructed signal Dz close to the true signal x

Unrolling: Compressive Sensing

$$\min_{z} \|Dz - x\|_2^2 + \lambda \|z\|_1$$

Keeps our reconstruction z sparse

Image Analysis with PDE Functionals

Goal: Define an energy functional on an image, then minimize functional to obtain segmentation:

$$\widehat{u} = \min_{u \in V,\, \Gamma \subseteq \Omega} E[u, \Gamma \,|\, u_0]$$

- u_0: image
- u: desired approximation
- $\Gamma \subset \Omega$: segmented section
- E: energy functional
- V: approximation space

Mumford-Shah Functional

$$E[u, \Gamma | u_0] = \alpha\nu(\Gamma) + \frac{\beta}{2}\int_{\Omega\setminus\Gamma} |\nabla u|^2 \, dx + \frac{\lambda}{2}\int_{\Omega} (K[u] - u_0)^2 dx$$

- u_0: image
- u: desired approximation
- $\Gamma \subset \Omega$: segmented section
- E: energy functional

PDEs to Unrolling: Preserving Sparsity

Compressive Sensing:

$$F[z|x] = \lambda \|z\|_1 + \|Dz - x\|_2^2$$

Image Analysis:

$$E[u, \Gamma|u_0] = \alpha\nu(\Gamma) + \frac{\beta}{2}\int_{\Omega\setminus\Gamma} |\nabla u|^2 \, dx + \frac{\lambda}{2}\int_{\Omega} (K[u] - u_0)^2 dx$$

PDEs to Unrolling: Matching Input and Output

Compressive Sensing:

$$F[z|x] = \lambda \|z\|_1 + \|Dz - x\|_2^2$$

Image Analysis:

$$E[u, \Gamma|u_0] = \alpha\nu(\Gamma) + \frac{\beta}{2}\int_{\Omega\setminus\Gamma} |\nabla u|^2 \, dx + \frac{\lambda}{2}\int_{\Omega} (K[u] - u_0)^2 dx$$