Radiomics Certificate, AAPM 2018

**Directors**
- Ahmed Hosny, Hugo Aerts, Dana-Farber Cancer Center
- Laurence Court, University of Texas MD Anderson Cancer Center

**Faculty**
- Xenia Fave, University of California San Diego
- Shouhao Zhou, University of Texas MD Anderson Cancer Center
- Carlos Cardenas, University of Texas MD Anderson Cancer Center
- Arvind Rao, University of Michigan
- Jeff Layton, NVIDIA
- Mark Hill, NVIDIA
- Chintan Parmar, Dana-Farber Cancer Institute
- Roman Zeineck, Dana-Farber Cancer Institute

1. Introduction to radiomics – including radiomics features and statistics
2. Machine learning for radiomics – intro to machine learning, deep learning
3. Convolution neural nets – including radiomics case studies
4. Deep learning lab (NVIDIA) – hands-on experience
5. Radiomics proffered abstracts – 12 radiomics papers
6. Deep learning with medical images – including 1-hour hands-on lab

**REMINDER:** Lab sessions are for Radiomics course registrants – bring your laptop (fully charged)!!

Introduction to Radiomics

- Introduction to radiomics – Laurence Court, University of Texas MD Anderson Cancer Center
- Radiomics features – Xenia Fave, University of California San Diego
- Statistics for radiomics – Shouhao Zhou, University of Texas MD Anderson Cancer Center

Photograph (1994) courtesy of Maryellen Giger

University of Chicago 1994 Prototype System for Computer-Aided Detection

Photograph (1994) courtesy of Maryellen Giger

LODWICK, G. S., et al. 1963. The coding of Rontgen images for computer analysis as applied to lung cancer, Radiology 81(2), 185–200
Learning Objectives

1. To introduce the goals and objectives of radiomics research
2. To describe where radiomics research is today
3. To understand the workflow when using quantitative image features for radiomics research
4. To understand the key statistical techniques used in radiomics

Imaging features and radiomics

- Radiologists identified 138 different imaging traits on contrast-CT scans of hepatocellular carcinomas (n=28)
- Filtered traits based on reproducibility and independence (>32)
- Searched for associations between expression of 6,732 genes (clustered) (microarray analysis) and combinations of imaging traits.
28 imaging traits could reconstruct 78% of gene expression profile (116 modules)

Imaging for precision medicine

Advantages of imaging for precision medicine
- Appearance is somehow related to tumor phenotype – and related outcomes
- Performed non-invasively
- Provides a 3D picture of the entire cancer
- Already performed in clinical practice
- Multiple times during treatment for diagnosis, staging, radiation oncology planning, response assessment
- Captures the cancer appearance over time (delta radiomics) and space

Disadvantages/challenges of imaging for precision medicine
- Proves the cancer at the macroscopic level
- Can be qualitative not quantitative
- Patient heterogeneity – means we need lots of data
- Heterogeneous acquisition protocol
- Comparisons between patients difficult
- Comparisons between same patient in time difficult
So, what is radiomics?

**Hypothesis:** Quantitative image features are related to underlying gene expression and phenotype

**Goals:**
- To provide a comprehensive quantification of the phenotype of the tumor
- To provide patient-specific predictions of their "outcome" given a specific treatment

The outcome could be genetic expression, treatment response (pathology), overall survival, freedom from metastases, .......

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**General Radiomics Hypothesis:** Quantitative image features are related to underlying gene expression and phenotype

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**Radiomics workflow**

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[Image of radiomics workflow diagram]

Figure adapted from Aerts et al., Nature Communications 2015
Decoding the tumor phenotype

Methodology

- Identify stable features
- Select most stable feature from each feature category
- Multivariate Cox proportional hazards regression model for prediction of survival
- Four final features:
  - Statistics energy — overall tumor density (intensity histogram)
  - Shape compactness — compactness of the tumor (shape)
  - Grey level nonuniformity — intratumor heterogeneity (texture)
  - Wavelet grey level nonuniformity HLH — heterogeneity after decomposing the image in mid-frequencies (wavelet)
Prognostic performance

Can we do this with PET images?

- 195 Patients, stage II NSCLC w/ definitive XRT
- 11 conventional prognostic factors
- MIM PETedge: Semi-automated delineation
- 47 Quantitative Image Features (QIFs) [IBEX]
- Clustering to try to identify multiple risk groups

Importantly, PET

- COM Energy: Measure of primary tumor SUV uniformity
  - Sum(Probability of unique combinations of SUV values between adjacent pixels)
- Solidity: Measure of local-regional disease dispersion
  - (Disease Volume/Convex Hull Volume)
Radiomics to determine appropriate treatments

- RT0G 0617 showed no benefit (possible harm) in dose escalation for stage III NSCLC patients
- What if there are sub-groups of patients that would benefit?

![Graph showing overall survival and high/low solidity, high/low energy](image)

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Radiomics workflow

- Imaging
- Segmentation
- Preprocessing
- Feature extraction
- Analysis
- Gene expression
- Clinical data

Figure adapted from Aerts et al, Nature Communications 2015

Deep learning for autocontouring

- Chose 2D approach with VGG-19 architecture

Necessary Modifications:
- 3 channel
- 0-255 range

Long, Shelhamer, Darrel
Fully Convolutional Networks
for Semantic Segmentation
IEEE CVPR 2015

Slide from Brian Anderson, MD Anderson

Cong, Dethamer, Damir
Fully Convolutional Networks
for Semantic Segmentation
IEEE CVPR 2015
Resources

- Many different tools for feature calculation, statistics, machine learning etc.
- Court et al, Computational resources for radiomics, Translational Cancer Research 5(4), 340-348, 2016
- 3D slicer/Pyradiomics – Aerts group’s python library and pipeline
- www.Radiomics.world – Radiomics Quality Score (Lambin group)

Summary

- Radiomics image features have potential for:
  - Improving risk stratification compared with conventional prognostic factors
  - Understanding genetic expression
  - Predicting patient-specific response to treatment (e.g. dose escalation)
- The use of these features is:
  - Non-invasive
  - Routinely obtained images
- Our understanding is still basic:
  - Why do specific image features work? – what are we actually detecting?
  - How can we optimize the features? – filtering, reproducibility
  - What about multimodality approaches? CT/PET/ANR
- We can expect results to improve as we improve our control of the various noise sources
- Also, new modeling/image handling techniques will improve models (especially deep learning)

Research group and collaborators

Our group (past and present)
- Joy Zhang
- Zhizhong Yang
- Dennis Mackin
- Rachel Ger
- Luke Hunter
- David Fried
- Jinzhong Yang
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- Rachel Ger
- Luke Hunter
- David Fried
- Jinzhong Yang

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- Anwul Rao

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- Anwul Rao

- Center for Radiation Oncology Research