Correlating Radiomics Information with Clinical Outcomes for Lung SBRT

Fang-Fang Yin, PhD
Duke University Medical Center

AAPM 2017 Denver CO

Disclosure

- This research is partially funded by a research grant from Varian Medical Systems

Acknowledgements

Radiation Oncology

- Kyle Lafata
- Jing Cai
- Jim Chang
- Ruiqi Geng
- Chris Kelsey
- Julian Hong
- Lei Ren
- Chunhao Wang
- Jackie Wu

Physics

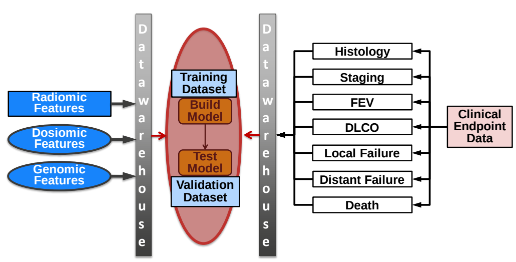
Jian-Guo Liu
Zhennan Zhou

Objectives

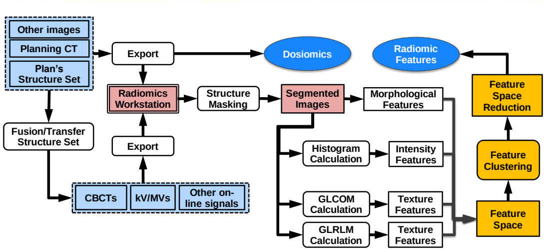
- Correlation study between patient specific radiomics data and clinical outcomes extracted from lung SBRT
- Techniques for extracting large amount radiomics data in CT and CBCT images used for lung SBRT
- Effective data modeling for treatment assessment and prediction in lung SBRT

4

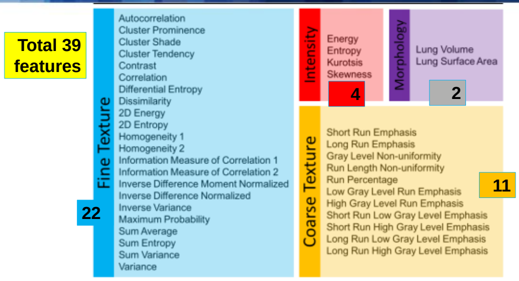
Application s to Lung SBRT



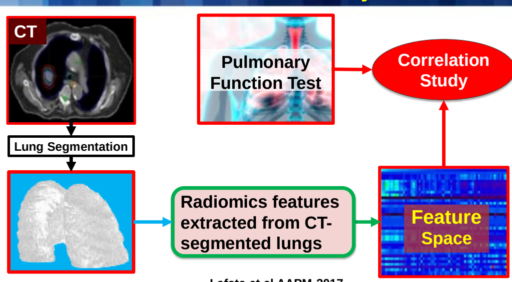
Example – Image/Data Flow



Sample Radiomic Features

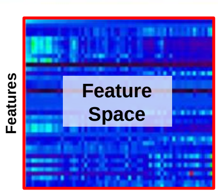


CT Radiomic Features and Pulmonary Function



Lafata et al AAPM 2017

Build A Pulmonary Radiomics Feature Space



Patients

- **Each column:** a particular patient's radiomic feature vector,

$$x_i = \langle x_1, x_2, \cdots, x_n \rangle$$

- **Collective feature vectors:** encode radiomic information extracted from a patient's CT-segmented lungs

Feature Analysis: Multivariate analysis using a novel clustering algorithm based on Quantum Langevin Clustering (QLC)

Lafata et al AAPM 2017

Feature Clustering: Quantum Langevin Clustering

Development of Quantum Langevin Clustering (QLC): 3 steps

Step 1: **Map radiomics feature vectors, x_i, to a function space, $\psi(x)$, by associating each feature with a Gaussian of width, σ, and constructing their sum (mapping from Euclidean space into Hilbert space):**

$$x_i = \langle x_1, x_2, \cdots, x_n \rangle \rightarrow \psi(x) = \sum_{i=1}^{m} e^{-\frac{1}{2\sigma^2}(x-x_i)^2}$$

- ✓ $\psi(x)$ represents probability density function of data
- ✓ Interpreted as a **quantum mechanical wavefunction**

Lafata et al AAPM 2017

Feature Clustering: Quantum Langevin Clustering

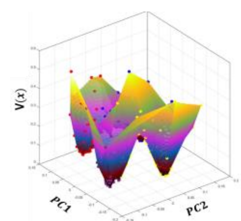
Step 2: **Inversely search for corresponding Potential Function, V(x)**

$$\psi(x) = \sum_{i=1}^{m} e^{-\frac{1}{2\sigma^2}(x-x_i)^2}$$

$$\downarrow$$

$$V(x) = \frac{\frac{\sigma^2}{2}\nabla^2\psi(x)}{\psi(x)} + E$$

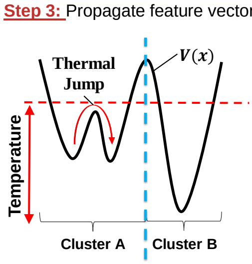
✓ Satisfies the **Schrodinger Equation** with solution $\psi(x)$



Lafata et al AAPM 2017

Feature Clustering: Quantum Langevin Clustering

Step 3: Propagate feature vectors through **V(x)** via Langevin dynamics



$$dx = p\,dt$$

$$dp = \underbrace{-\nabla V(x)dt}_{\text{Global Force Term}} - \underbrace{\gamma p\,dt}_{\text{Damping Term}} + \underbrace{\sqrt{2\gamma k_B T}\,dB}_{\text{Brownian Motion}}$$

- ✓ **Global Force**: Potential gradient acts globally to push vectors *downhill*
- ✓ **Brownian Motion**: Acts locally to help vectors thermally jump local barriers into locations otherwise forbidden, controlled by **Temperature T**

Lafata et al AAPM 2017

Correlation Study between QLC and Lung Function

Correlation study using QLC: Map a relationship between the radiomic feature space and pulmonary function test (PFT)

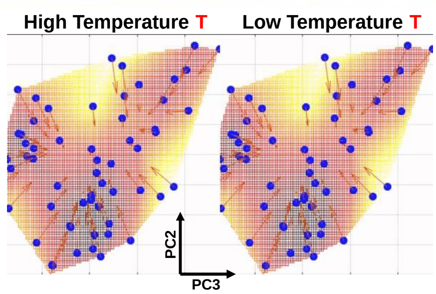
Feature Space
- ✓ 65 patients
- ✓ 39 features

← QLC →

Pulmonary Function Test Data
- ✓ Forced Expiratory Volume 1 (FEV1)

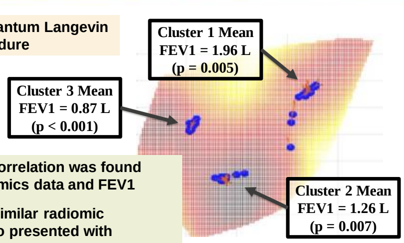
Lafata et al AAPM 2017

Demonstration of Clustering Analysis



Results using QLC for Clustering Analysis

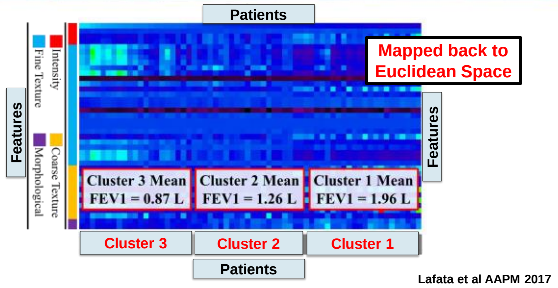
Final state of Quantum Langevin Clustering procedure



- ✓ A significant correlation was found between radiomics data and FEV1
- ✓ Patients with similar radiomic signatures also presented with comparable spirometry measurements

Lafata et al AAPM 2017

Results: Clustering Analysis

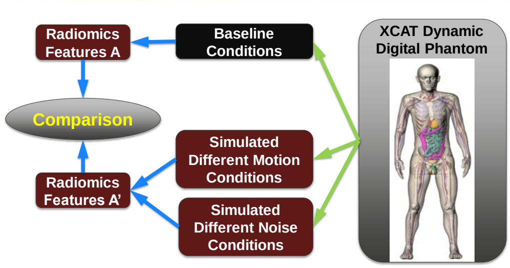


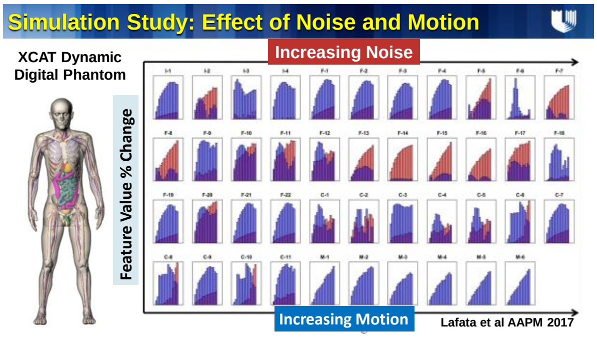
Lafata et al AAPM 2017

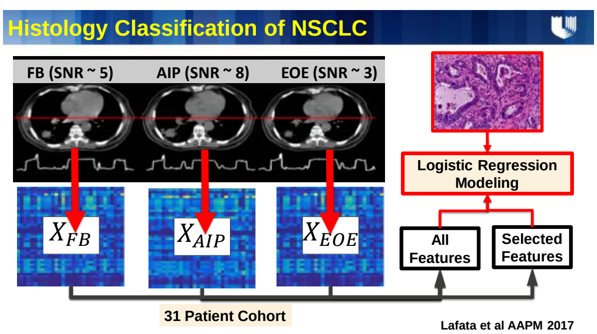
Sensitivity Analysis of Radiomics

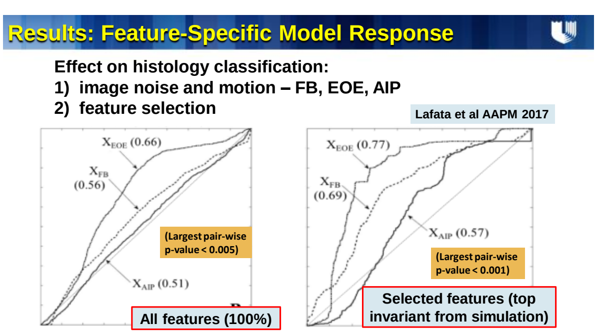
- Effect of imaging noise
- Effect of motion
- Effect of HU inhomogeneity

Simulation Study: Effect of Noise Motion



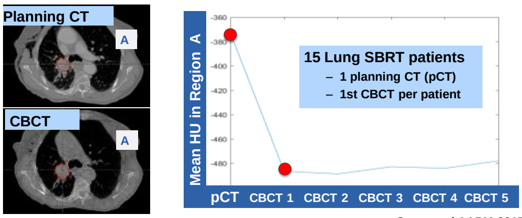

Simulation Study: Effect of Noise and Motion
XCAT Dynamic Digital Phantom
Increasing Noise
Feature Value % Change
Increasing Motion
Lafata et al AAPM 2017


Histology Classification of NSCLC
FB (SNR ~ 5)
AIP (SNR ~ 8)
EOE (SNR ~ 3)
X_{FB}
X_{AIP}
X_{EOE}
Logistic Regression Modeling
All Features
Selected Features
31 Patient Cohort
Lafata et al AAPM 2017


Results: Feature-Specific Model Response
Effect on histology classification:
1) image noise and motion – FB, EOE, AIP
2) feature selection
Lafata et al AAPM 2017
X_{EOE} (0.66)
X_{FB} (0.56)
(Largest pair-wise p-value < 0.005)
X_{AIP} (0.51)
All features (100%)
X_{EOE} (0.77)
X_{FB} (0.69)
X_{AIP} (0.57)
(Largest pair-wise p-value < 0.001)
Selected features (top invariant from simulation)

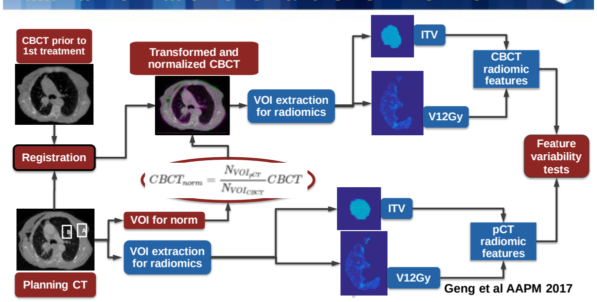
Effect of Inhomogeneous HU between CT/CBCT

- Radiomics feature variations on CBCT and planning CT
- Harmonization between planning CT (pCT) and on-board CBCT images



Geng et al AAPM 2017

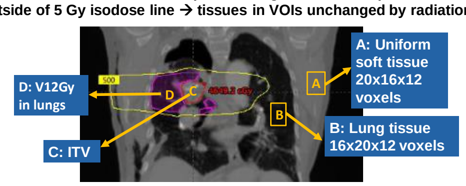
Data Harmonization of CT and CBCT: Workflow



Geng et al AAPM 2017

Volumes of Interest (VOIs) Selection for Normalization

VOIs at the same locations on pCT and registered CBCT (VOI A & B: outside of 5 Gy isodose line → tissues in VOIs unchanged by radiation



Wilcoxon signed rank test (p<.05) and Bonferroni correction (DOF=55) were used to test each pair of feature and to identify number of variable features before and after each harmonization

Geng et al AAPM 2017

Feature Variability Reduction on ITV

# of variable features before harmonization	Features	VOI: Soft tissue (A)	VOI: Lung tissue (B)	VOI: Average of A & B	VOI: ITV
1	Gray level histogram	0%	0%	0%	-100%
4	Gray level co-occurrence	25%	-200%	50%	50%
7	Gray level run length	85.7%	-14.2%	50%	42.9%
8	Gray level size zone	37.5%	-12.5%	12.5%	37.5%
0	Neighborhood gray tone difference	0%	-100%	0%	-100%

For radiomics calculation in ITV, harmonization with VOI in soft tissue or average of 2 is more effective in feature variability reduction

25

Feature Variability Reduction on Lung V12Gy

Features	# of variable features before harmonization	VOI: Soft tissue (A)	VOI: Lung tissue (B)	Average of A & B	VOI: V12Gy
Gray level histogram	1	100%	0%	100%	100%
Gray level co-occurrence	0	0%	-1400%	0%	0%
Gray level run length	2	0%	-100%	50%	100%
Gray level size zone	1	0%	-200%	0%	0%
Neighborhood gray tone difference	0	0%	-200%	0%	-200%

For radiomics calculation in V12 Gy in lungs, harmonization with average of 2 VOIs provided the highest efficiency of feature variability reduction.

Geng et al AAPM 2017

26

Summary

- **Radiomics features are useful for treatment assessment**
- **Radiomics features are affected by motion, noise and data variability**
- **Quantification of radiomics features are important for their clinical applications**

27

Thank you for your attention

28

Q1 Which of following is not a radiomics feature?

a. Grey-level co-occurrence matrix correlation
b. Grey-level co-occurrence matrix energy
c. Grey-level co-occurrence matrix homogeneity
d. Morphology
e. Mean dose

Answer: **e**

Ref: **Sarah A. Mattonen et al, Detection of Local Cancer Recurrence After Stereotactic Ablative Radiation Therapy for Lung Cancer: Physician Performance Versus Radiomic Assessment. Int J Radiation Oncol Biol Phys, Vol. 94, No. 5, pp. 1121-1128, 2016 http://dx.doi.org/10.1016/j.ijrobp.2015.12.369**