Quantitative Texture Characterization of Interstitial Lung Disease using Generative Adversarial Networks

Joseph Boogun Choi
Graduate Program at the Department of Industrial and Systems Engineering
Graduate Research Assistant at the Visual Intelligence Laboratory
Diagnosis of IPF:

- High-resolution computed tomography (HRCT)
- Patterns such as ground-glass opacity, reticular, and honeycombing guide the diagnosis of IPF
- However, definite diagnosis requires the presence of honeycombing (Wells, 2011)
- Relies on subjective perception. Empirical threshold in decision making
  - Inter-observer agreement: 37.9% & 48.3% (Antunes et al. 2010; Ranghu et al. 2018)

Honeycomb Quantification

Previous approaches:

• Histogram kurtosis / density measures: (Wu, 2019; Kim, 2015)
  • Mean lung attenuation, variance, skewness, entropy, median, kurtosis, etc.
  • Cons: heavily influenced by CT dose, slice thickness, and alteration of texture by protocol

• Density measure based Machine Learning: (Zavaletta, 2007; Foncubierta, 2012)
  • Utilized clustering algorithms, support vector machine, random forest, kNN
  • Cons: still highly depend on the density measures

• Data-driven Deep Learning: (Anthimopoulos, 2019; Anthimopoulos, 2016)
  • Not hand-crafted features, but features learned from the data
  • Cons: highly depend on the label of the data, but qualitative visual assessment is limited by inter-observer variability. (Lynch, 2015) Prone to overfitting and low interpretability
Objectives

- To design a **data-driven** model to **reduce subjective bias** due to inter-observer variance
- To design a data-driven model that can learn heterogeneous textures of honeycombing
- To **localize and quantify honeycombs** in the HRCT images
- To have a rapid, objective measurement of disease extent and change over time
- To develop **image-based biomarkers for diagnosis, prognosis, and monitoring** of response to therapy in IPF
  - Fibrotic scoring system
Our methods: takes 3 steps

- generative model: learns to generate IPF textures ("Learn by make")
- encoder model: learns to map CT image into texture parameters
- classifier model: distinguishes given CT image is honeycomb or not
**Honeycomb Quantification**

Generative Model

\[ p = G(u) \]

Parameter Space \( \mathbb{R}^{15} \)

Texture Manifold \( \mathbb{R}^n \)

Training Samples

Idea of generative learning method

Result of learned texture manifold
Honeycomb Quantification

Depicts smooth texture manifold

Depicts controllability of Generative model

Generative Model

$\mathbb{R}^n$

$(1 - s) s$

$(1 - t) t$

$(1 - t)$

$(1 - s)$

$s$

$t$
Honeycomb Quantification

Encoder Model

Parameter Space $\mathbb{R}^{15}$

Texture Manifold

Encoder

$n$-dimensional Parameter Space $\mathbb{R}^n$

Texture Manifold

Idea of Encoder Training

Generating training samples for encoder
Honeycomb Quantification

Classifier Model

$\mathbb{R}^n$

Texture Manifold

Idea of classifier

Details of classifier training

Encoder

Likelihood of honeycombing
Honeycomb Quantification

Classifier Model

Honeycomb
Healthy Lung
Other textures

Ground Truth
Predicted
Honeycomb Quantification

Conclusion:

• Unsupervised quantification model:
  • Reduced the overfitting => model is more robust and generalizable
• Interpretable model:
  • Controllable parameters to explore the texture manifold
  • Visualize the corresponding texture from the parameters

Future works:

• Compare performance with other State-of-the-art models
• Treatment outcome prediction
Thank you