3D Riesz–wavelet Based Covariance Descriptors for Texture Classification of Lung Nodule Tissue in CT

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Motivation + Contribution

- (**Statistical**) feature extraction and representation
- Dictionary **modelling of lung/nodule** tissue areas
- **Classification** of lung nodule areas
  (solid / ground glass opacity -GGO / healthy)

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Goal and application

Supervised learning of region classes from **texture**
Robustness to size and shape **variations**
Applications: **tissue modelling**, classification, segmentation

Related work

Clinical domain

- 3D visualization and annotation software
- Manual delineation with expertise of clinicians

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Computer vision + Machine Learning domain

- 3D features: Riesz transform, 1st and 2nd order visual cues
- 3D descriptors: MCOV, 3D-SIFT, SHOT, THRIFT...
- Linear/non-linear (un)supervised classification methods: CNN, Kernel-SVMs, Sparse coding, Bag-of-visual features...

Intuition - features

Riesz-wavelet transform as texture features [1]

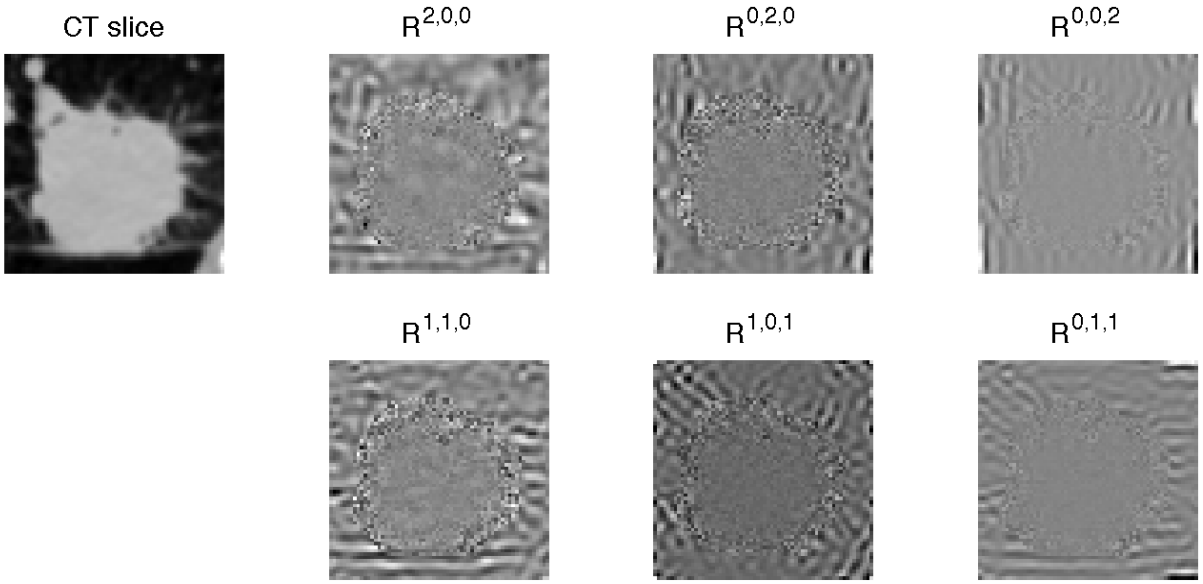


Figure 1: Lung nodule CT slice with corresponding Riesz filter responses

[1] A. Depeursinge *et al.*, "Lung Texture Classification Using Locally–Oriented Riesz Components", in MICCAI 2011

Intuition - feature representation (**in 3D**)

3D Riesz-covariance models

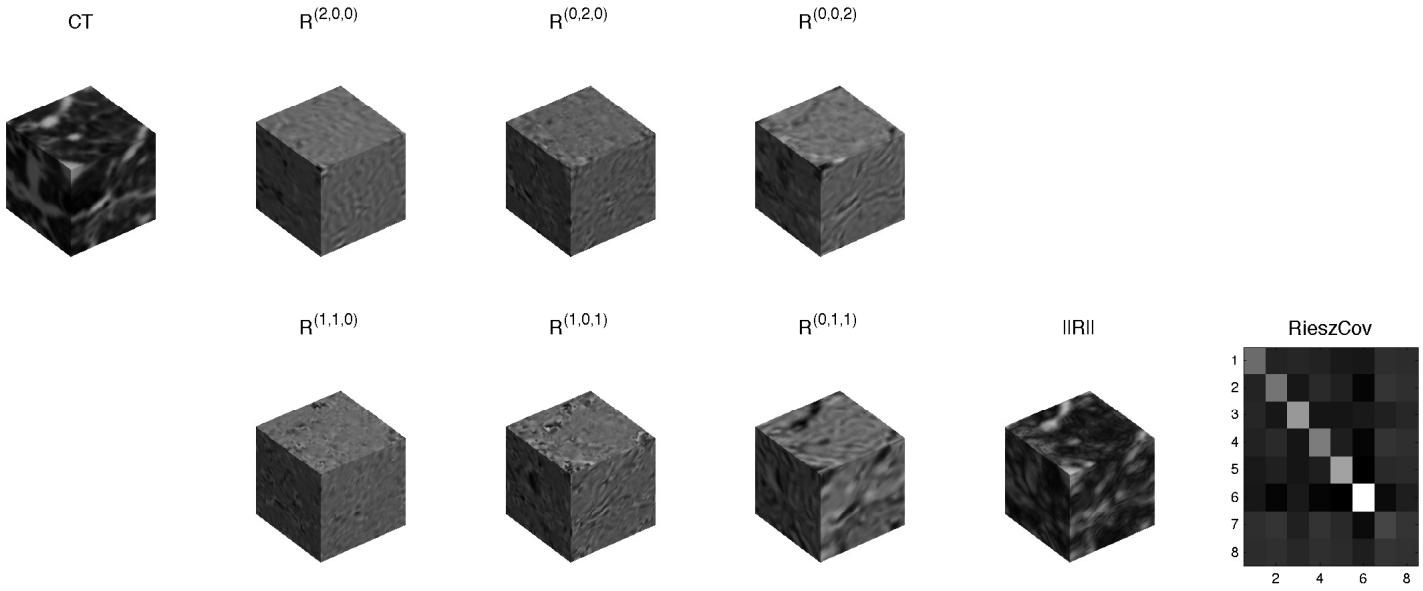
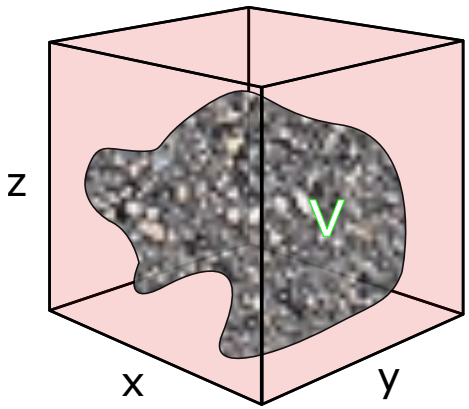


Figure 2: 3D CT volume and associated Riesz-covariance descriptor

3D Riesz-Covariance descriptors



$$\Phi(ct, v) = \{\phi_{x,y,z}, \forall x, y, z \in v\} \tag{1}$$

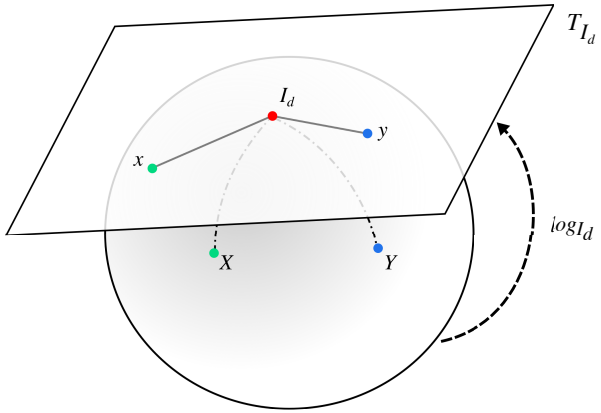
$$\phi_{x,y,z} = \left(\mathcal{R}_{x,y,z}^{(n_1,n_2,n_3)}, \|\mathcal{R}\|_{x,y,z}, ct_{x,y,z}\right) \tag{2}$$

$$RieszCov\left(\Phi(ct, v)\right) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\phi_{x,y,z} - \mu_\phi)\right)\left(\phi_{x,y,z} - \mu_\phi)\right)^T, \tag{3}$$

Covariance model benefits

- Common framework for statistical data modelling.
- Features $\equiv$ samples of $n-$dim joint distributions.
- Second order moment statistics ($n \times n$ covariance matrices).
- Covariances manifold (Sym_d^+) $\Rightarrow$ analytical modelling Riemannian space ported machine learning techniques.

Covariance descriptors - Sym_d^+ Riemannian space



$$x = \log_Y(X) = Y^{\frac{1}{2}} \log\left(Y^{-\frac{1}{2}} X Y^{-\frac{1}{2}}\right) Y^{\frac{1}{2}} \tag{4}$$

$$\hat{x} = vect(x) = (x_{1,1}, x_{1,2}, \ldots, x_{1,d}, x_{2,2}, x_{2,3}, \ldots, x_{d,d}) \tag{5}$$

$$\delta(X, Y) = \sqrt{Trace\left(\log\left(X^{-\frac{1}{2}} Y X^{-\frac{1}{2}}\right)\right)} \tag{6}$$

Data gathering

Ground-truth:

- 95 patients (from Stanford Hospital and Clinics)
- Biopsy-proven early stage non-small cell lung carcinoma
- Nodule regions delineated in CTs by clinicians
- Processing with MATLAB software:
  isotropic voxels of 0.8 mm^3

Data samples

GGO vs. Solid lung nodule tissue components (vs. healthy lung)

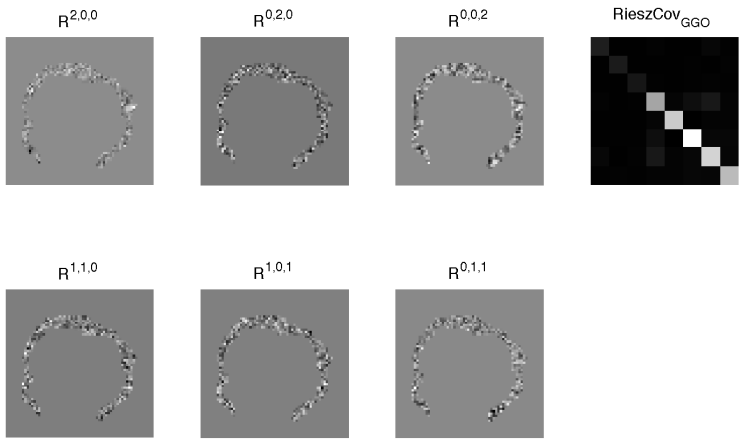


Figure 3: Lung nodule Riesz filter responses - GGO component

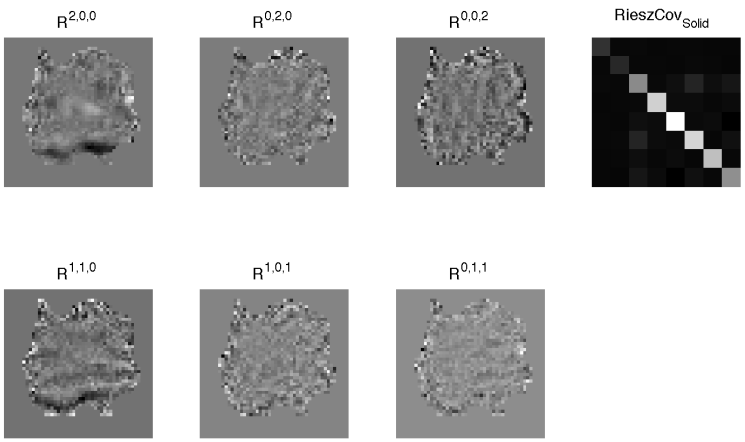
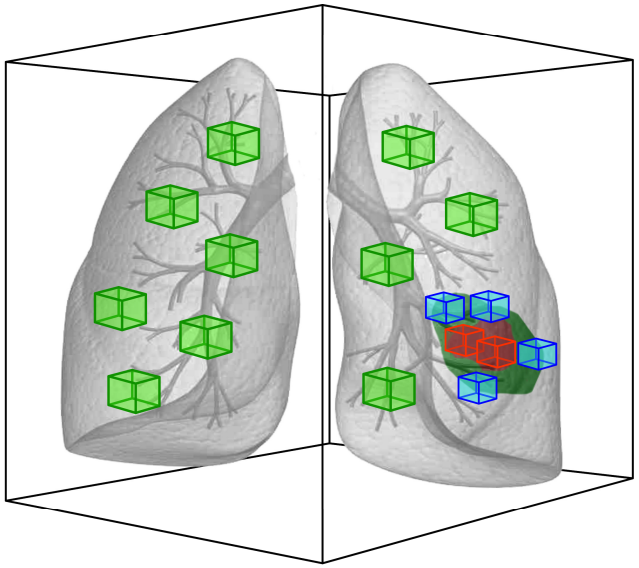


Figure 4: Lung nodule Riesz filter responses - solid component

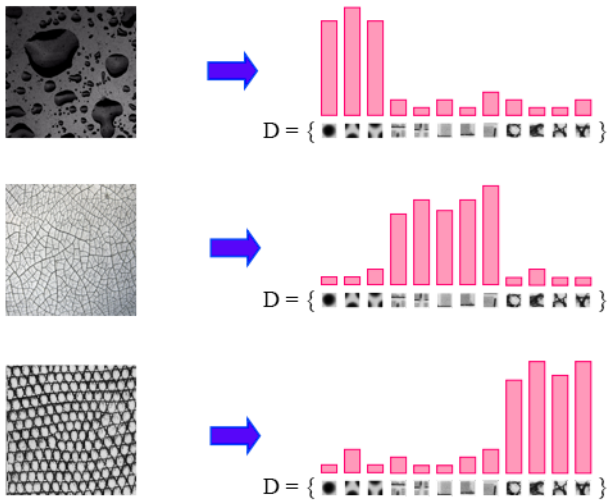
Bag-of-covariances

Standard bag-of-visual features paradigm.
Sub-sampling of partial class regions for a complete dictionary modelling



Bag-of-covariances

- *Dictionary* $D \equiv \hat{x}^{c}_{v,p} = vect(\log_{I_d}(RieszCov^{C}_{V,P}))$
- Training set: modelling frequencies of *words* in D



- Classification decision: $class(ct) = \text{argmin}_i\, D(h_{ct}, h_i)$

Experimental setup

Data sets:

- 35 patients for model learning, 60 for test set.
- 60 words per class (dictionary size, $3 \times 60 \times 35 = 3600$)
- 10-fold cross-validation.

Quantitative evaluation w.r.t. ground-truth:

- Avg. sensitivity (TP / TP+FN) = **82.2%**
- Avg. specificity (TN / TN+FP) = **86.2%**

Conclusions

- Computer vision and Machine Learning to the service of medical knowledge
- Statistical design for a robust solution
- Easily extendible framework

Future work

- More patients and bigger data collection
- Different modelling contexts for concrete problems
- Exploit the covariance-based descriptor space for different Machine Learning techniques (clustering, classification, regression...)

Thanks for your attention

Questions?

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