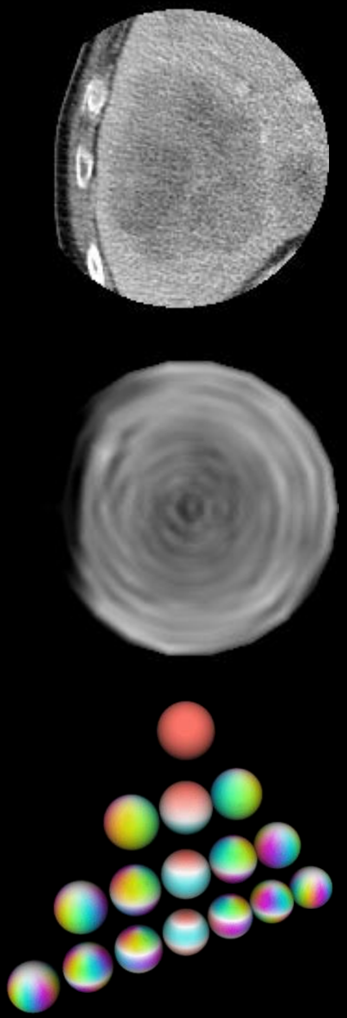
Friday, November 8th - Montreal, QC, Canada



Computational Methodology for Image-based Outcomes Prediction in Liver Cancer

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Challenges for ML in Radiology

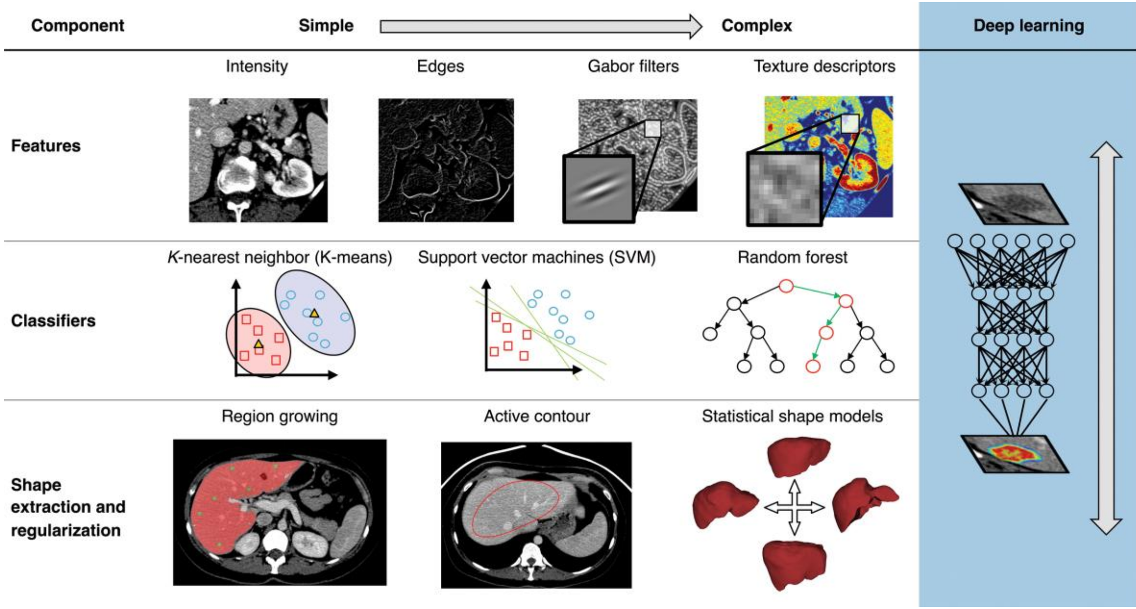
Outcomes Prediction after Therapy using Imaging

Radiomics:

- Require segmentation
- Often done on one 2D slice
- Time consuming for a volume

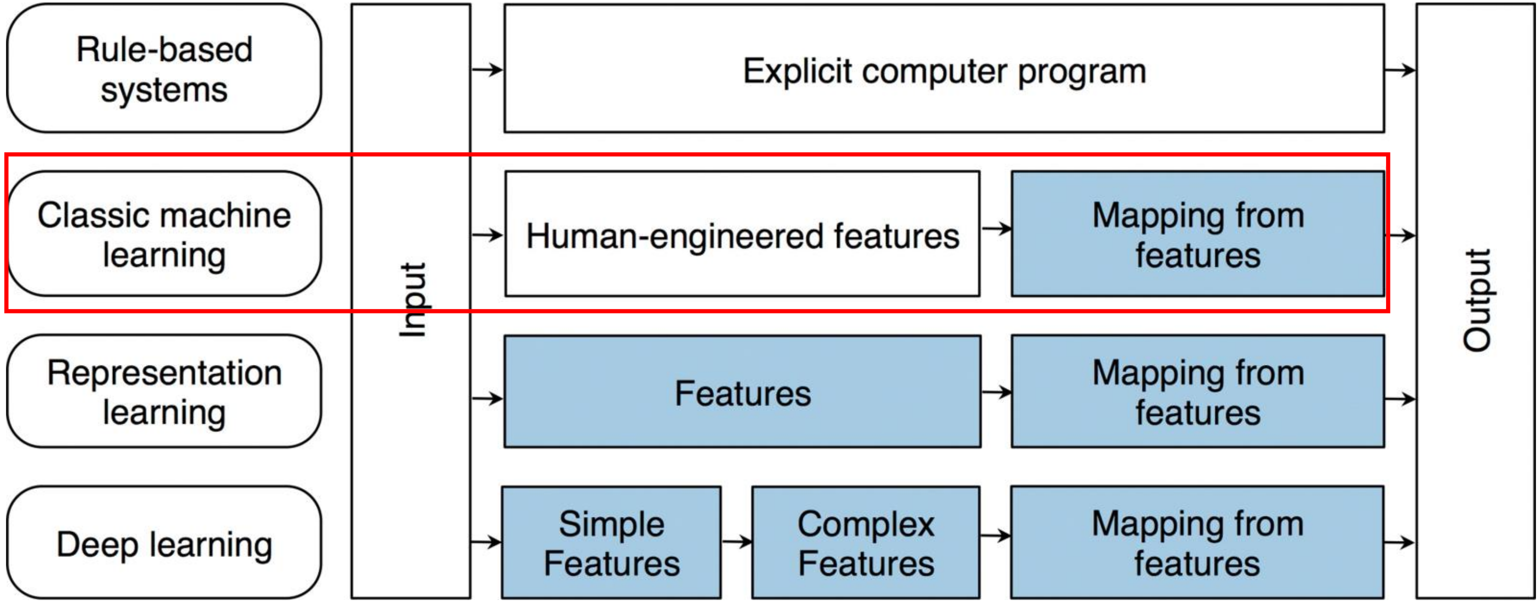
Deep learning:

- Requires huge training set
- Sensitive to image orientation
- 3D can be really computationally heavy



Chartrand G *et al*. Radiographics. 2017Nov-Dec;37(7):2113-2131.

Feature-based Classification

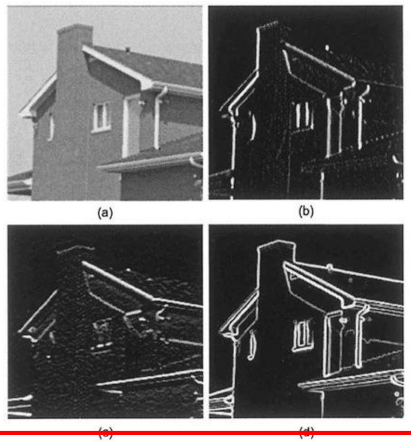


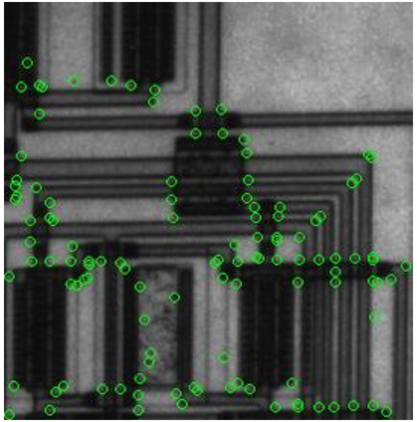
Chartrand G *et al*. Radiographics. 2017Nov-Dec;37(7):2113-2131.

Human-engineered Features

Local Image Descriptors

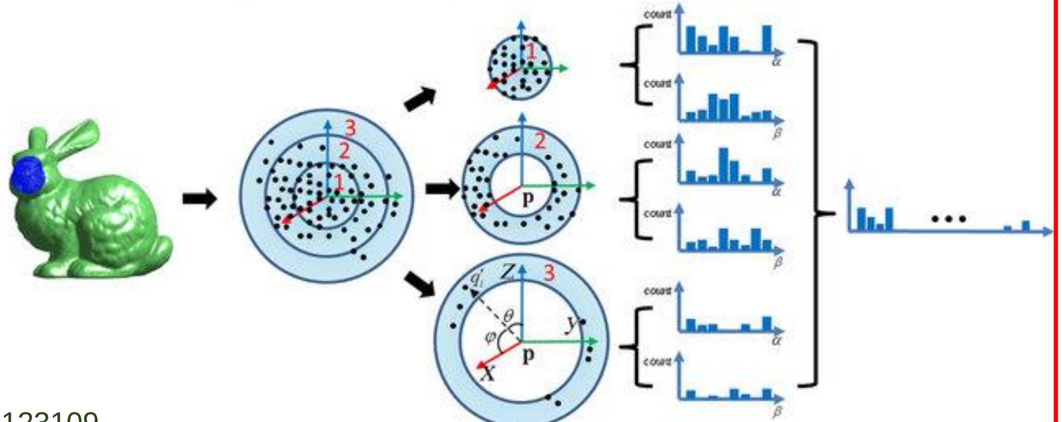
- Same size than the original image
- Enhance textures in images
- Can facilitate automated detection of features for image classification





Non-Local Image Descriptors

- Compact description of a volume
- Allows faster image classification with minimal loss of information
- No need for explicit segmentation



Rongrong L *et al*. Optical Engineering. 2017Dec; 56(12)123109.

Hydrogen-like Atom

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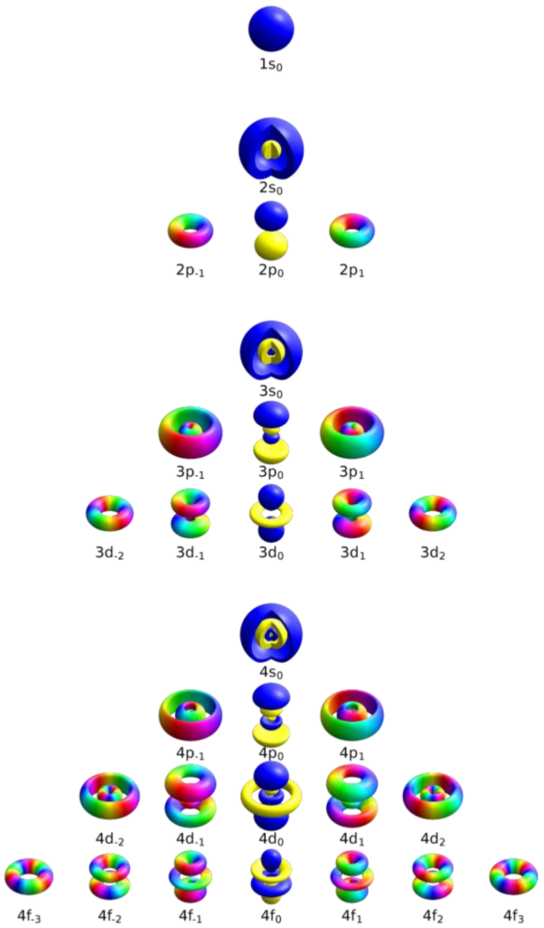
Schrödinger Equation Solutions

- Coefficients of the angular basis:
  Spherical Harmonics

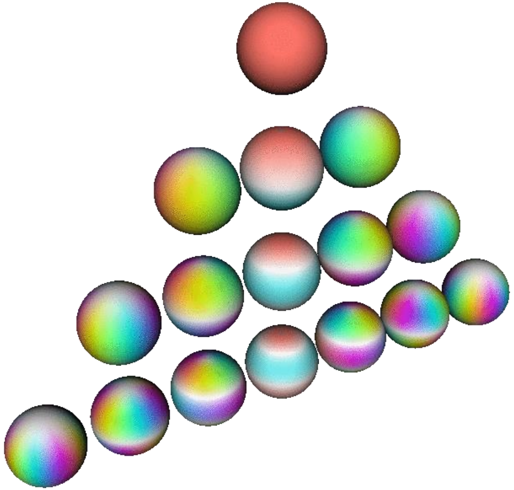
- Coefficients of the radial basis:
  Associated Laguerre Polynomials



Angular Basis

Laplace's Spherical Harmonics Functions $Y_l^m(\theta, \varphi)$

- Angular part of the complex electronic cloud structure of atoms
- Three quantum numbers n, l, m
- Combined with a radial basis, they can fully describe complex shapes



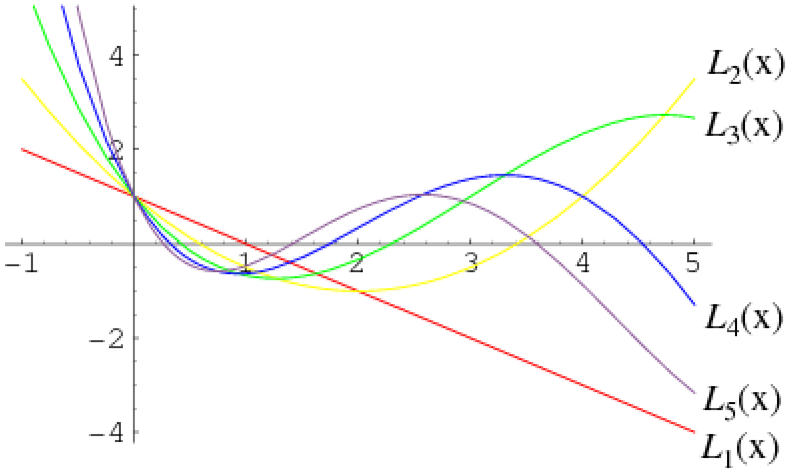
http://icgem.gfz-potsdam.de/vis3d/tutorial

Radial Basis

From H. Skibbe *et al*

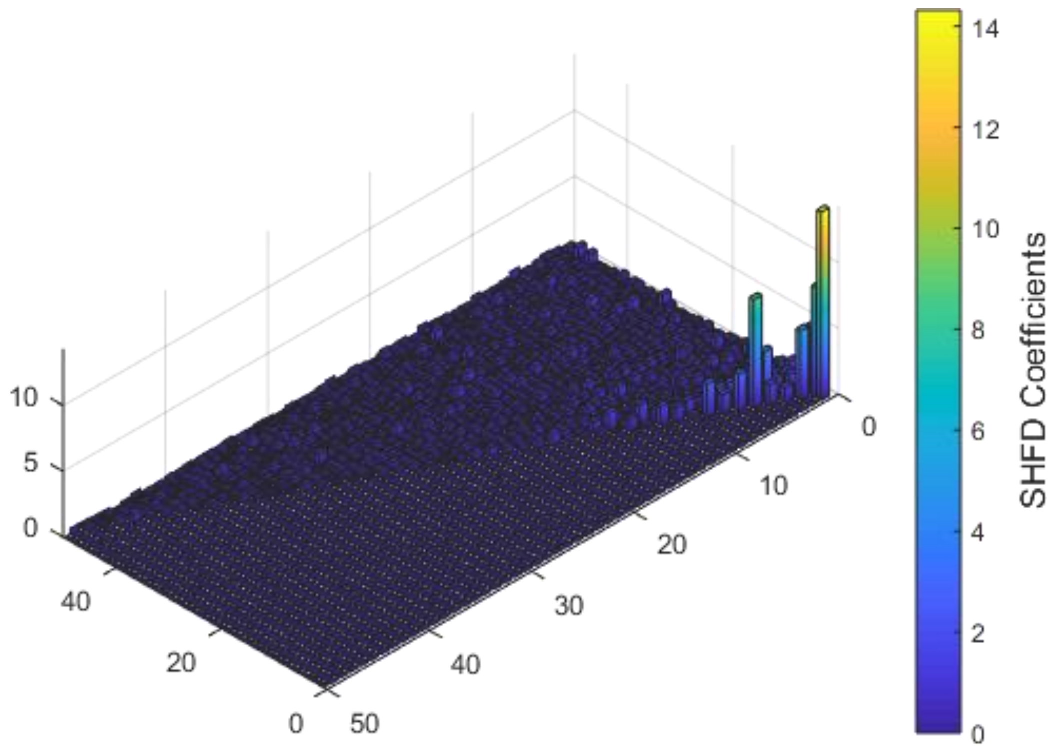
- Damped Fourier expansion as radial basis $w_k^R(r)$
- Computationally efficient choice for replacing associated Laguerre polynomials (really expensive)

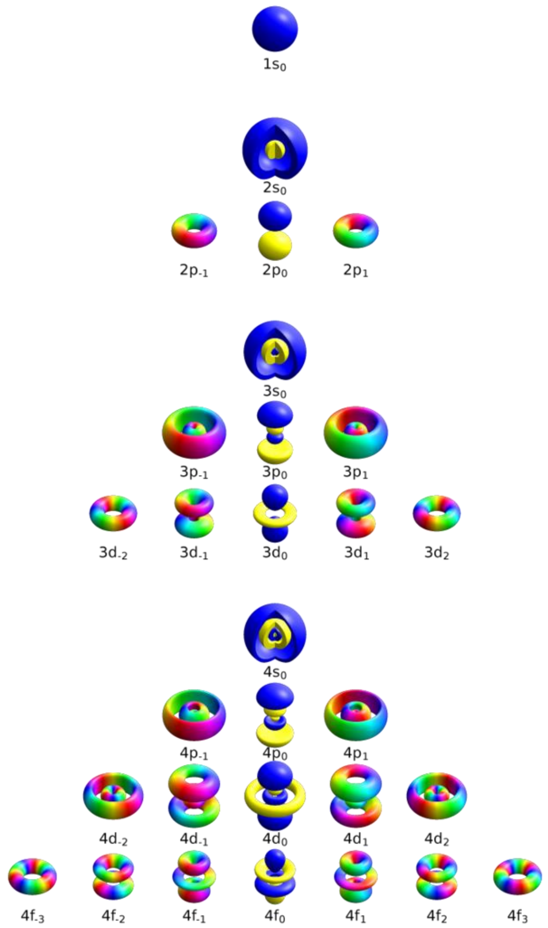
$$w_k^R(r) = \frac{1}{\sqrt{R}} e^{2\pi i k r \frac{1}{R}}$$



Skibbe H et al.,in Proc. of the 3DIM,12th IEEE ICCV 2009

Spherical Harmonics Fourier Descriptors

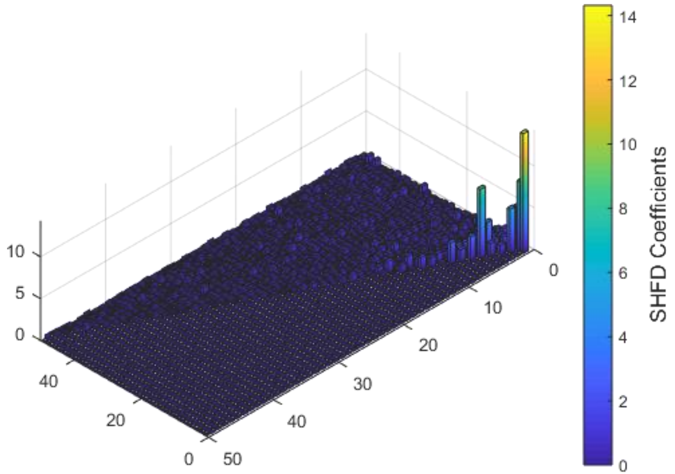


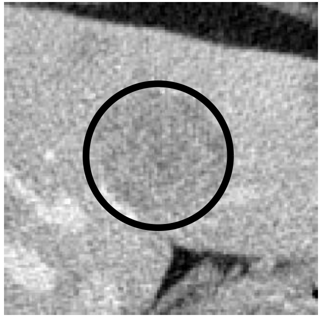


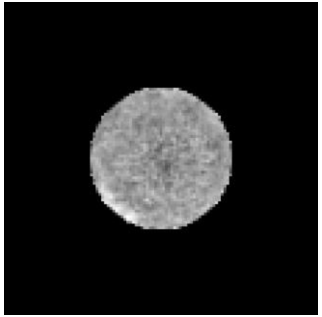
Tumor Modeling

Hypothesis

- Underlying tumour information can be encoded in spherical harmonics Fourier decomposition coefficients
- No need to segment: just select the center of the tumour and expand to a radius that will englobe the whole tumour

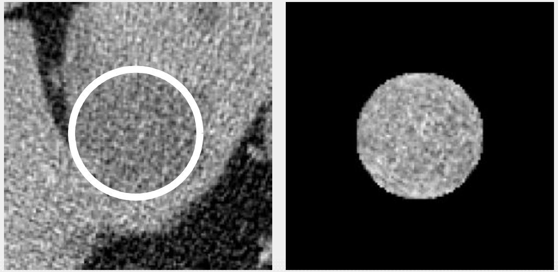


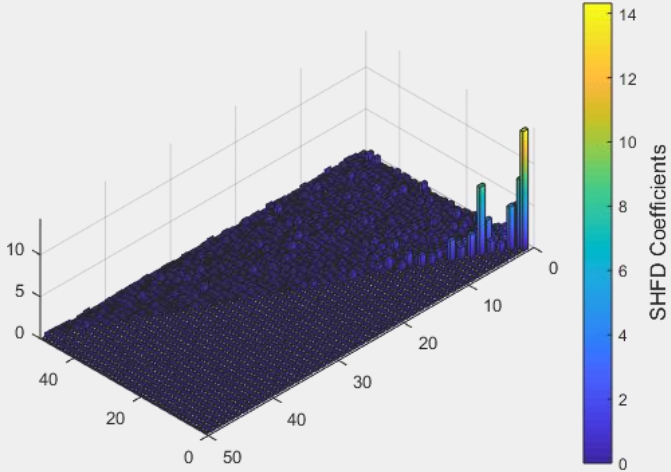


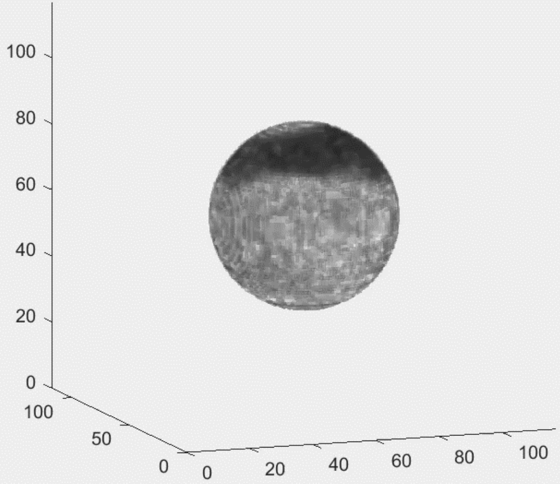


Example

- ≈100,000 voxels in segmented tumour volume
- Could be represented by 50 x 50 matrix,2,500 → evaluated in seconds
- Computationally efficient for classification (40 times smaller!)



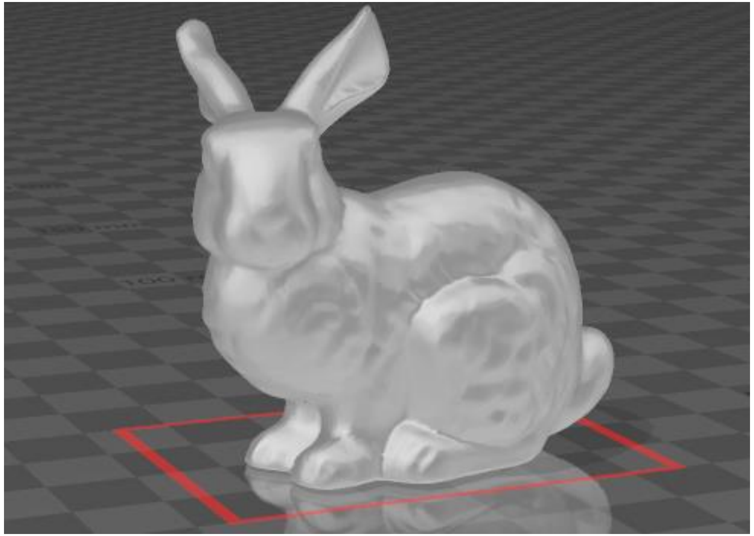




Tumor Modeling

Rationale

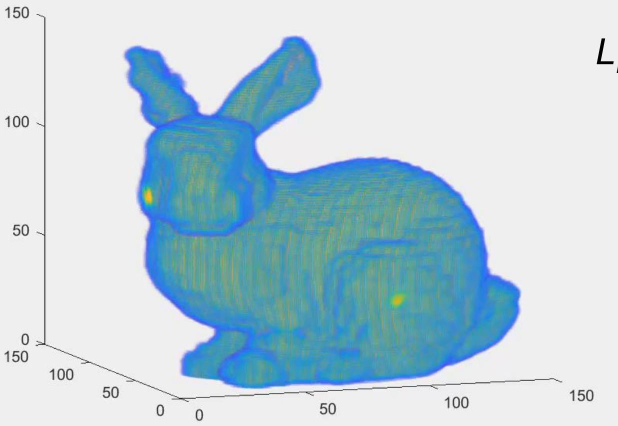
- Already been shown that using only these coefficients with no other prior information on the volume, we can reconstruct complex structures with minimal loss of information



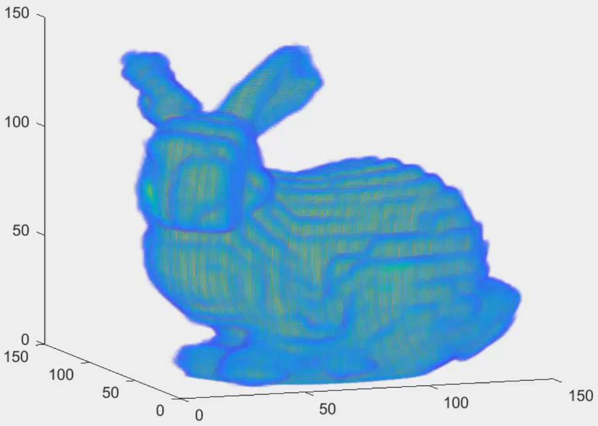
M Turk. www.cc.gatech.edu.

Population

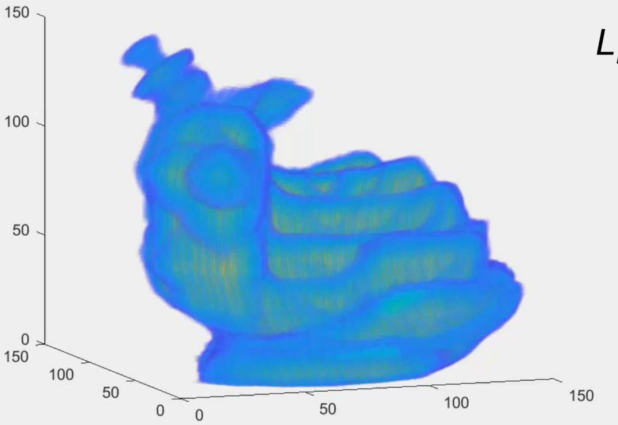
$L_{max} = 50$



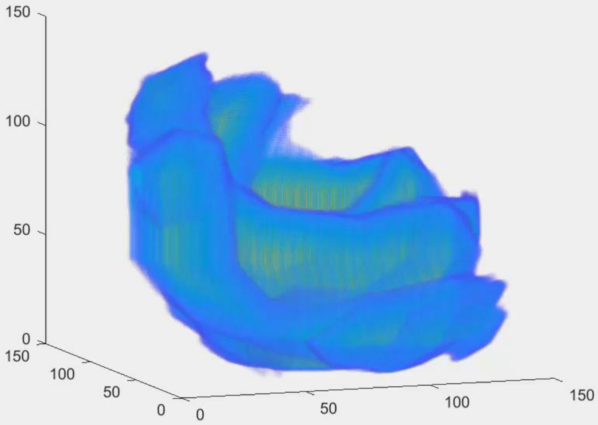
$L_{max} = 25$



$L_{max} = 10$

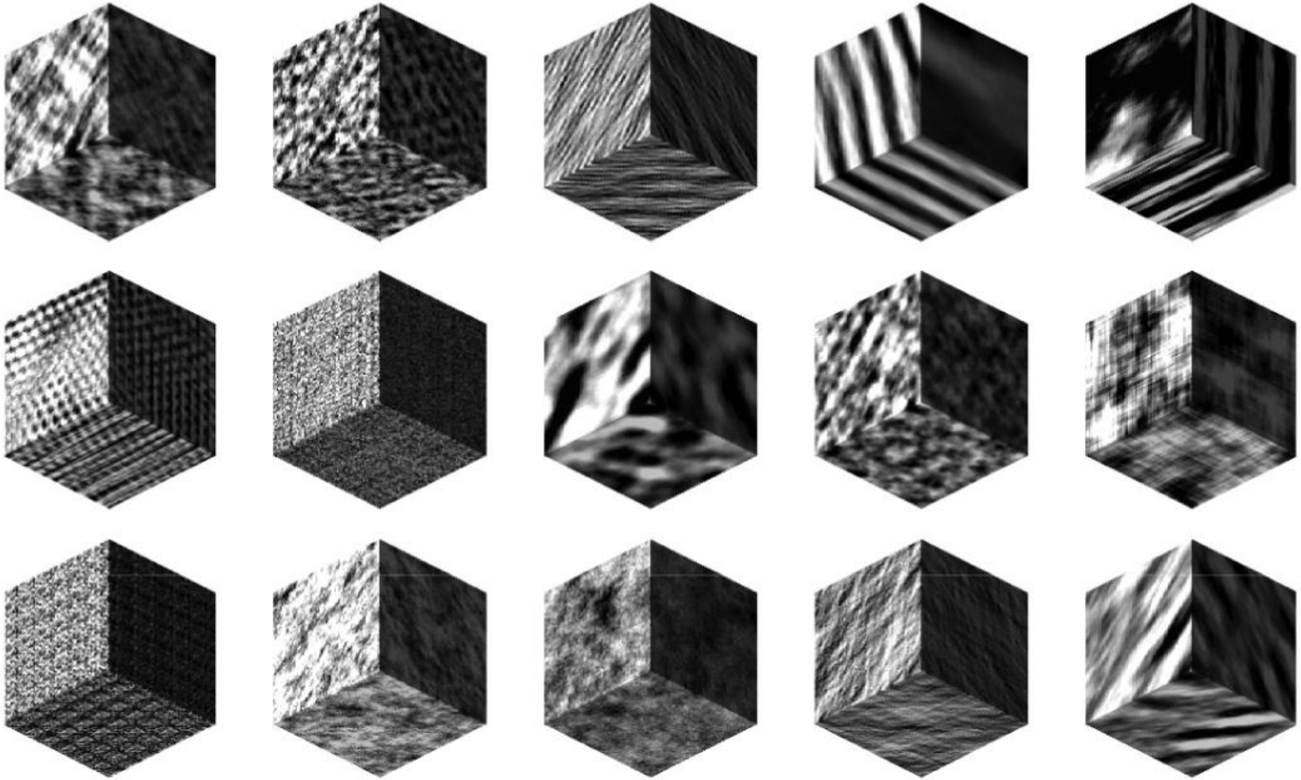


$L_{max} = 5$



RFAI Benchmark Dataset

Fourier Texture Dataset



L Paulhac. 4th International Conference on Computer Vision Theory and Applications. pp 135-141. 2009.

Statistical Analyses

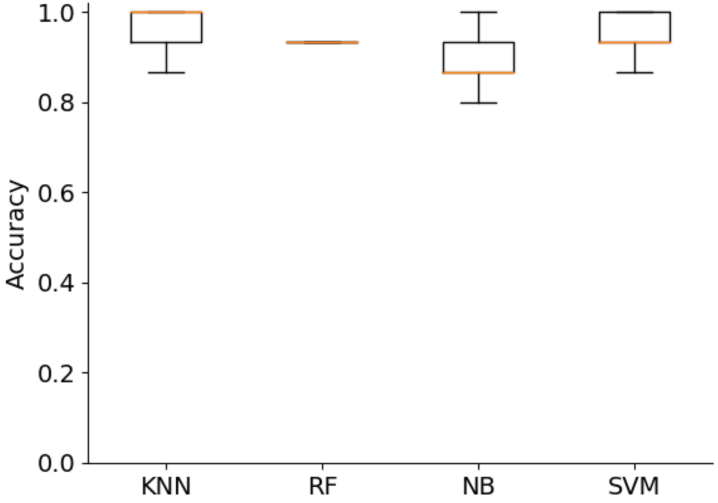
McGill

- Classification Performance Evaluated with 4 Machine Learning-based Classifiers:
  - *K-nearest Neighbors (KNN)*
  - *Random Forest (RF)*
  - *Gaussian Naive Bayes (NB)*
  - *Support Vector Machines (SVM)*
- Cross-validated Metrics with 95% Confidence Interval:
  - *Accuracy*

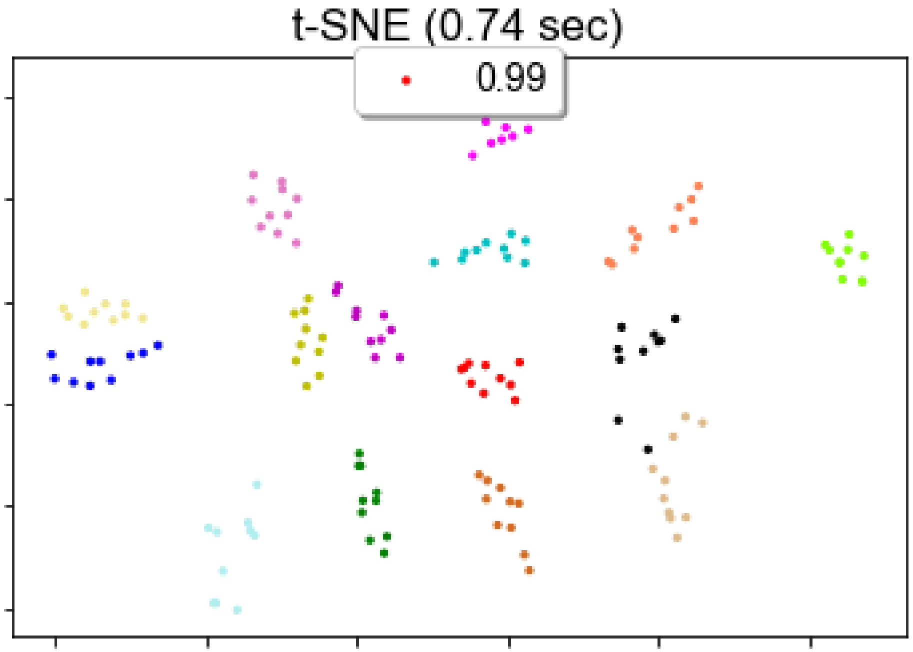
Preliminary Results (Fourier Texture)

McGill

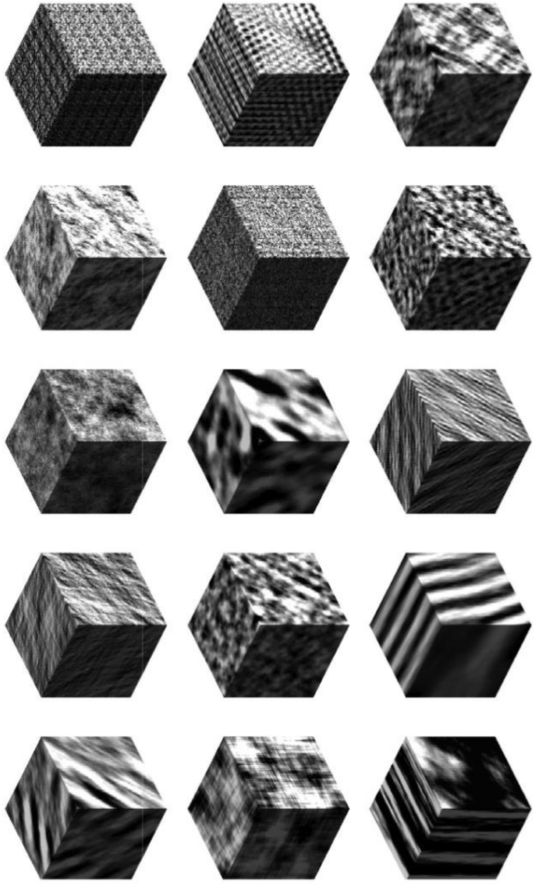
Data	ML-Classifier	Accuracy
Fourier (L_{max} = 50)	KNN	0.97 ± 0.05
	RF	0.93 ± 0.04
	NB	0.86 ± 0.08
	SVM	0.94 ± 0.05



T-dist. Stochastic Neighbor Embedding

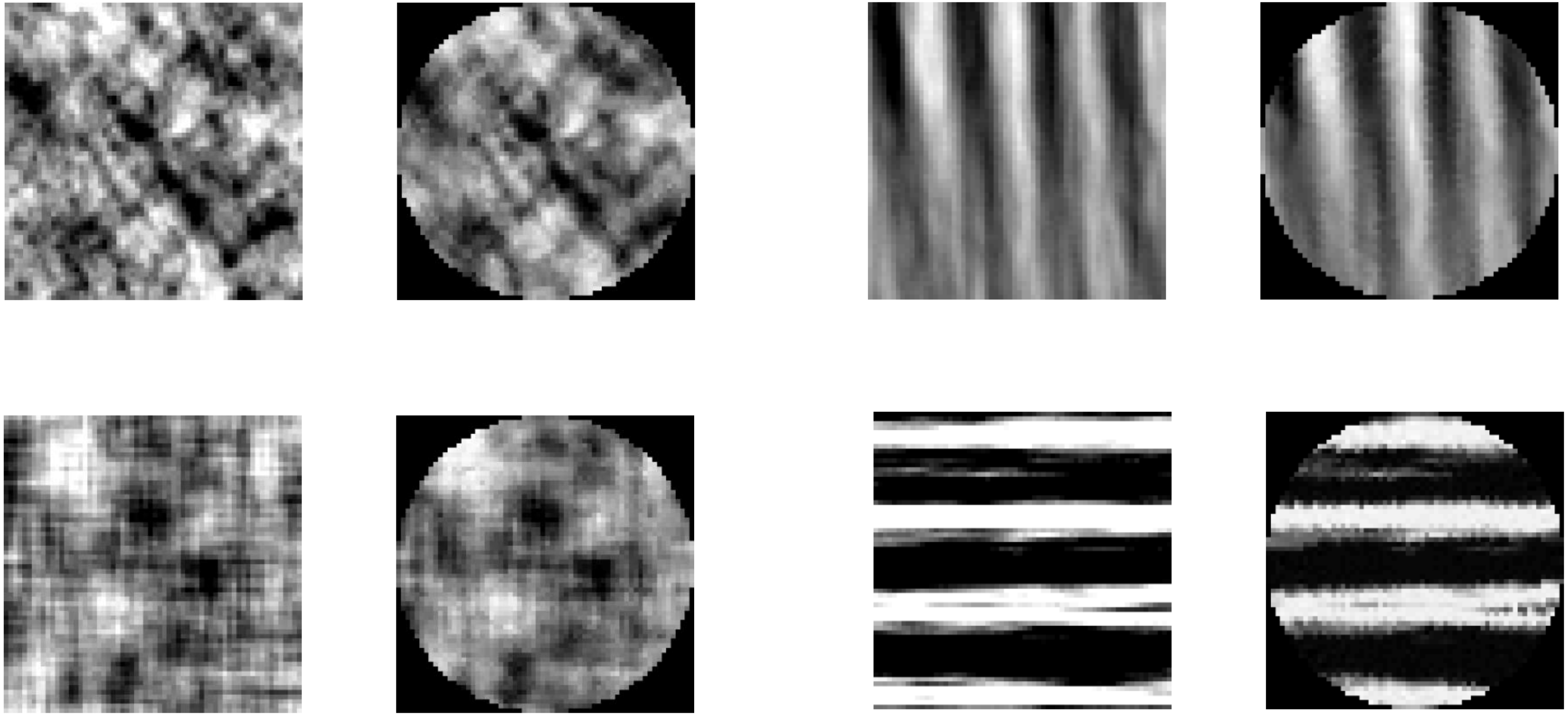


Accuracy of 0.99 with Linear Discriminant Analysis



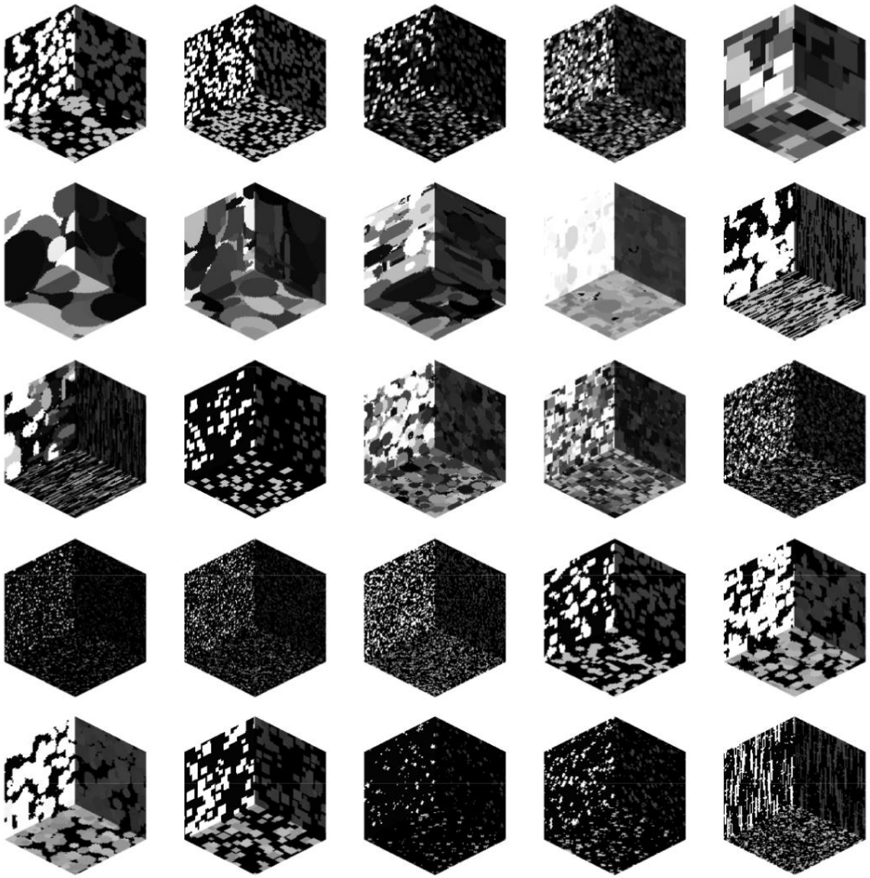
Fourier Texture Reconstructions

$L_{max} = 50$



Geometric Texture Dataset

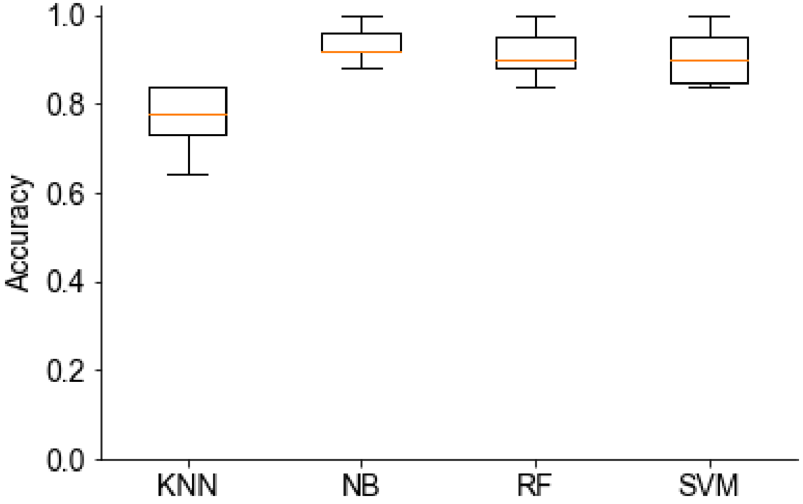
McGill



L Paulhac. 4th International Conference on Computer Vision Theory and Applications. pp 135-141. 2009.

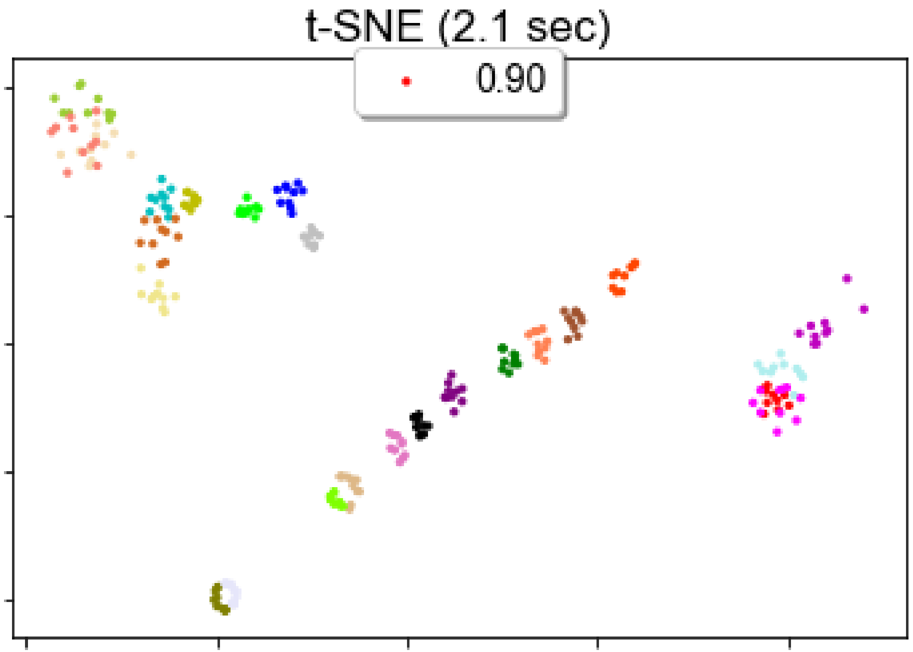
Preliminary Results (Geometric Texture)

Data	ML-Classifier	Accuracy
Geometric (L_{max} = 50)	KNN	0.77 ± 0.06
	RF	0.94 ± 0.04
	NB	0.92 ± 0.05
	SVM	0.91 ± 0.05

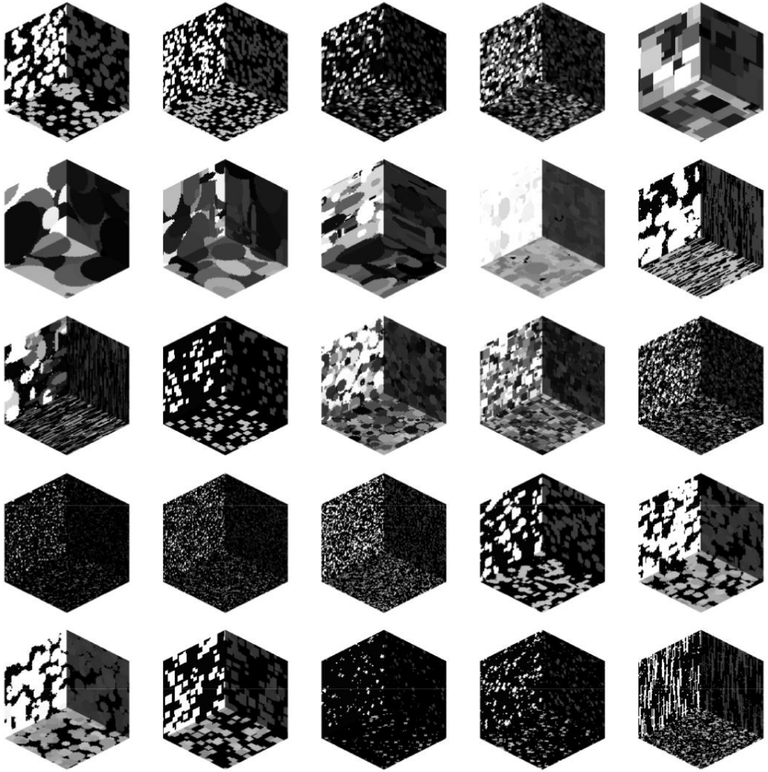


T-dist. Stochastic Neighbor Embedding

McGill

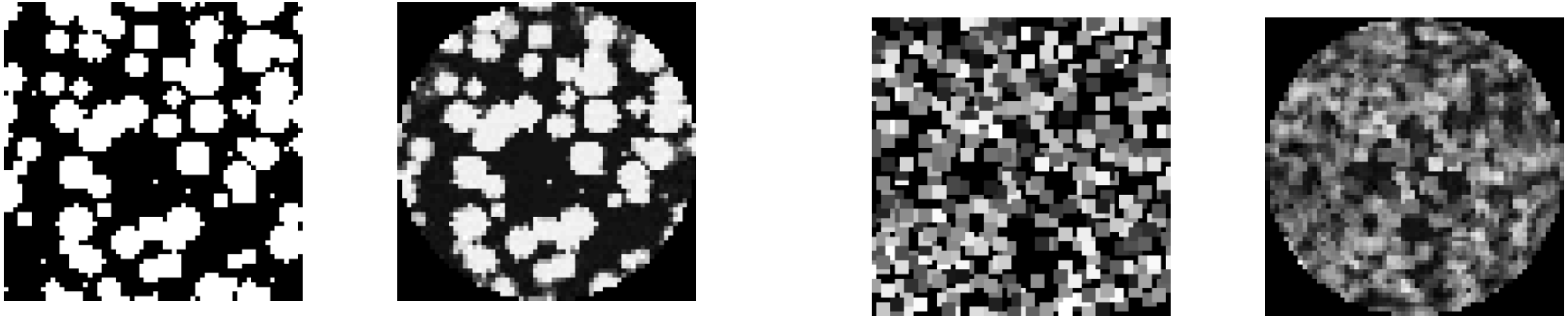


Accuracy of 0.90 with Linear Discriminant Analysis

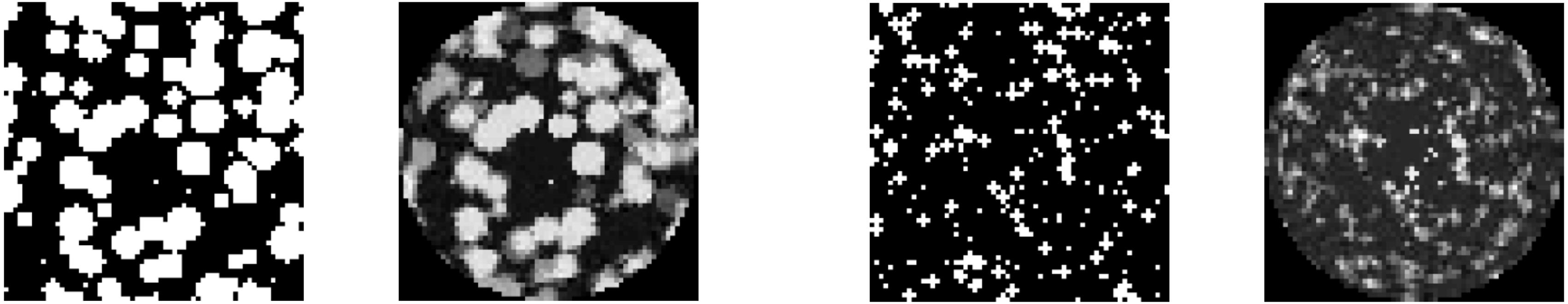


Geometric Texture Reconstructions

L_{max} = 150



L_{max} = 50

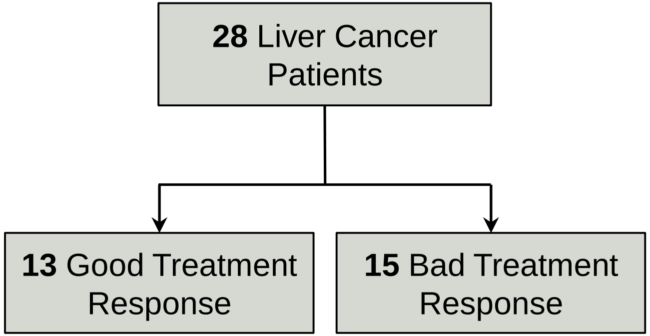


Liver Tumours Dataset

Preliminary Population

Liver Tumours

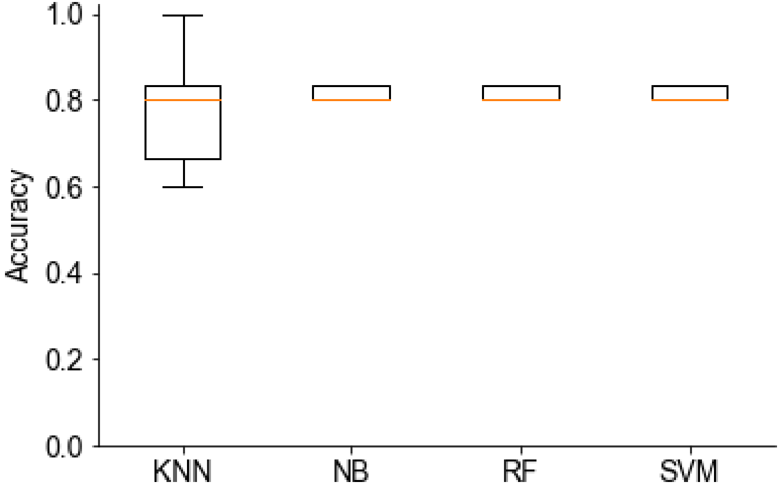
- Baseline CT scan prior to treatment
- Follow-up CT scan 2 months after treatment (outcomes 6 months after)
- SHFD evaluated on baseline data to see if it was enough to predict treatment response



Preliminary Results (Fourier Texture)

McGill

Data	ML-Classifier	Accuracy
Liver with STA Toolbox (L_{max} = 50)	KNN	0.78 ± 0.10
	RF	0.83 ± 0.06
	NB	0.83 ± 0.06
	SVM	0.83 ± 0.06

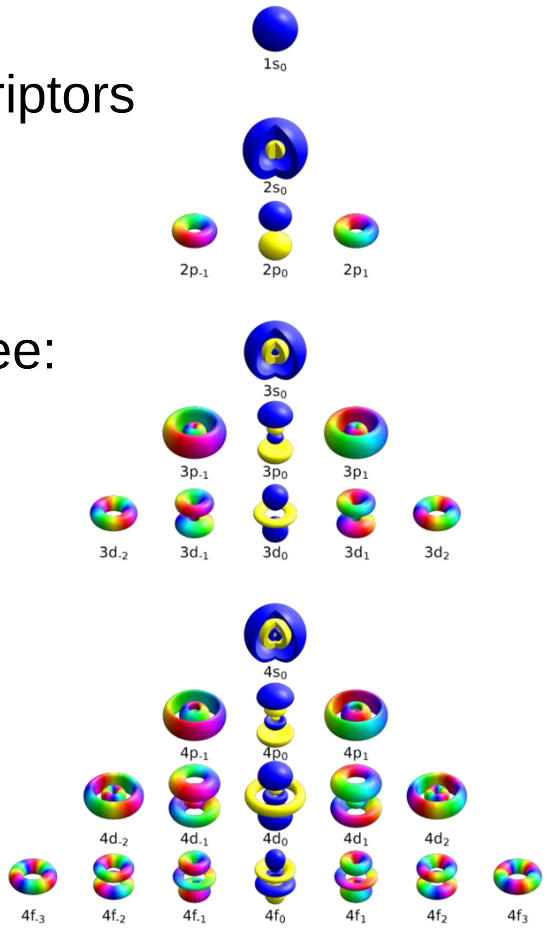


Conclusions

McGill

- Provided compact rotation-invariant image descriptors
  - fast classification
  - no need for segmentation

- Need to apply this tool to more tumour data to see:
  - How it performs in a larger dataset?
  - Can we get similar or better results than state-of-the-art radiomics (on segmented medical images)?



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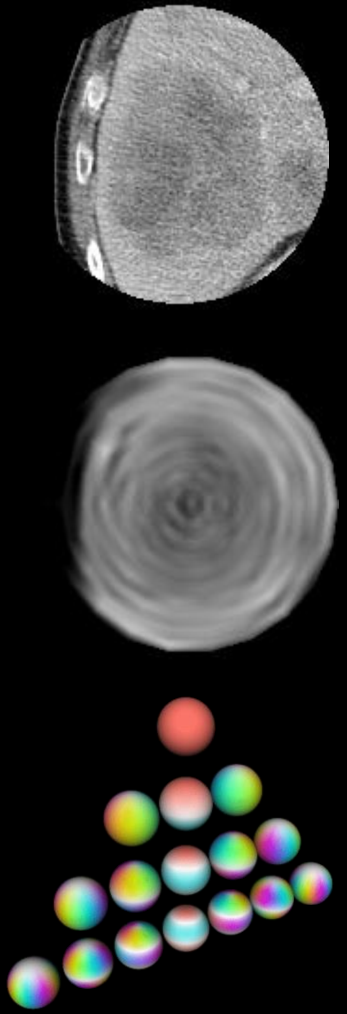

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- Ozan Ciga
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- Caroline Reinhold
- Reza Forgani

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Appendix

Spherical Harmonics Fourier Descriptors

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Sphere around tumour → Cartesian to spherical coordinates → SHFD 3D matrix (L x 2L x R) → Spherical tensor products (3 types) → L1-norm on the 3rd dimension R and concatenate

$$
\begin{aligned}
c_{\ell 0}^{Rk} &= \left|\mathrm{Real}\left(\left(\mathbf{a}_\ell^{Rk} \bullet_0 \mathbf{a}_\ell^{Rk}\right)^{\frac{1}{2}}\right)\right| \\
c_{\ell 1}^{Rk} &= \left|\mathrm{Imag}\left(\left(\mathbf{a}_\ell^{Rk} \bullet_0 \mathbf{a}_\ell^{Rk}\right)^{\frac{1}{2}}\right)\right| \\
c_{\ell 2}^{Rk} &= \left(\mathbf{a}_\ell^{Rk} \bullet_0 \mathbf{a}_\ell^{R,-k}\right)^{\frac{1}{2}} = \langle \mathbf{a}_\ell^{Rk}, \mathbf{a}_\ell^{Rk} \rangle^{\frac{1}{2}} \\
&= \|\mathbf{a}_\ell^{Rk}\|
\end{aligned}
$$

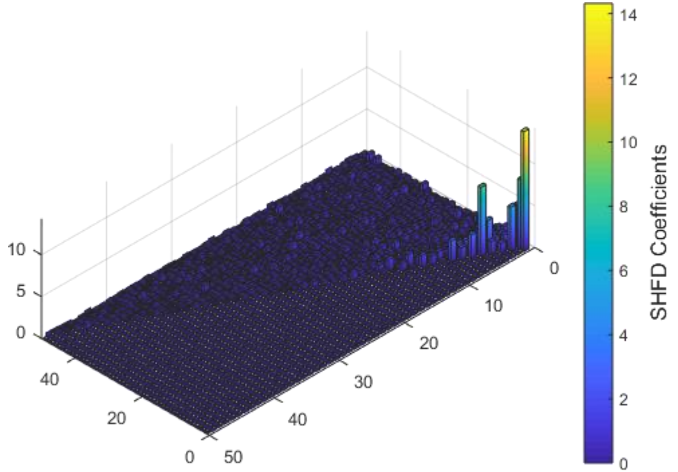
Skibbe H et al.,in Proc. of the 3DIM,12th IEEE ICCV 2009

Spherical Harmonics Fourier Descriptors (SHFD): $\mathbf{F}_{KL}$

- *phase information* of the coefficient is preserved in c_{l0}^{Rk} and c_{l1}^{Rk}
- c_{l2}^{Rk} represents the *energy bands* for l and k

$$
\begin{aligned}
c_{\ell 0}^{Rk} &= \left|\mathrm{Real}\left(\left(\mathbf{a}_\ell^{Rk} \bullet_0 \mathbf{a}_\ell^{Rk}\right)^{\frac{1}{2}}\right)\right| \\
c_{\ell 1}^{Rk} &= \left|\mathrm{Imag}\left(\left(\mathbf{a}_\ell^{Rk} \bullet_0 \mathbf{a}_\ell^{Rk}\right)^{\frac{1}{2}}\right)\right| \\
c_{\ell 2}^{Rk} &= \left(\mathbf{a}_\ell^{Rk} \bullet_0 \mathbf{a}_\ell^{R,-k}\right)^{\frac{1}{2}} = \langle \mathbf{a}_\ell^{Rk}, \mathbf{a}_\ell^{Rk} \rangle^{\frac{1}{2}} \\
&= \|\mathbf{a}_\ell^{Rk}\|
\end{aligned}
$$

$$
\mathbf{F}_{KL} = \{\mathbf{c}_0^{0\,T}, \cdots, \mathbf{c}_\ell^{Rk\,T}, \cdots, \mathbf{c}_L^{RK\,T}\}
$$



Skibbe H et al.,in Proc. of the 3DIM,12th IEEE ICCV 2009

Spherical Harmonics

McGill

Laplaces's Spherical Harmonics Functions $Y_l^m(\theta, \varphi)$

- Elevation angle θ
- Azimuthal angle φ
- Associate Legendre polynomials $P_l^m(\cos\theta)$
- Azimuthal quantum number l (from atomic physics)
- Magnetic quantum number m

$$Y_l^m(\theta, \phi) = \sqrt{\frac{2l+1(l-m)!}{4\pi(l+m)!}}\, P_l^m(\cos\theta)e^{im\phi} \qquad P_l^m(x) = \frac{(-1)^m}{(2^l l!)}(1+x^2)^{\frac{m}{2}}\frac{(d^{l+m})}{(dx^{l+m})}(x^2-1)^l$$

Prior Literature

McGill

H. Skibbe *et al*

- SPHARM as angular basis $f(\theta, \varphi)$ with coefficients b_{ln}
- Damped Fourier expansion as radial basis $w_k^R(r)$
  - Orthonormal basis for functions on interval $[0, R]$
- Expansion of function $f(\boldsymbol{r})$ defined on a sphere
  - with the expansion coefficients a_l^{Rk} and the orthonormal basis functions $E_{lm}^{Rk}(\boldsymbol{r})$

$$f(\theta,\phi) = \sum_{\ell=0}^{\infty} \sum_{m=-\ell}^{m=\ell} b_{\ell m} Y_m^\ell(\theta,\phi)$$

$$= \sum_{\ell=0}^{\infty} (\mathbf{b}_\ell)^T \mathbf{Y}^\ell(\theta,\phi)$$

$$w_k^R(r) = \frac{1}{\sqrt{R}} e^{2\pi i k r \frac{1}{R}}$$

$$f(\mathbf{r}) = \sum_{k=-\infty}^{k=\infty} \sum_{\ell=0}^{\ell=\infty} \sum_{m=-\ell}^{m=\ell} a_{\ell m}^{Rk} E_{\ell m}^{Rk}(\mathbf{r})$$

$$= \sum_{k=-\infty}^{k=\infty} \sum_{\ell=0}^{\ell=\infty} (\mathbf{a}_\ell^{Rk})^T \mathbf{E}_\ell^{Rk}(\mathbf{r})$$

$$E_{\ell m}^{Rk}(\mathbf{r}) = Y_m^\ell(\theta,\phi) w_k^R(r) \frac{1}{r}$$

H. Skibbe et al.,in Proc. of the 3DIM 2009, part of the 12th IEEE ICCV 2009

Prior Literature

McGill

H. Skibbe *et al*

- Expansion separately performed
  - angular part $Y_m^l(\theta,\varphi)$ using a spherical harmonic transformation
  - radial part $w_k^R(r)\frac{1}{r}$ using an ordinary 1D Fourier transformation
- Expansion coefficients a_l^{Rk}
  - weighting $f(\boldsymbol{r})$ by distance from centre r

H. Skibbe *et al*

- Expansion separately performed
  - angular part $Y_m^l(\theta,\varphi)$ using a spherical harmonic transformation
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H. Skibbe *et al*

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H. Skibbe *et al*

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H. Skibbe *et al*

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  - radial part $w_k^R(r)\frac{1}{r}$ using an ordinary 1D Fourier transformation
- Expansion coefficients a_l^{Rk}
  - weighting $f(\boldsymbol{r})$ by distance

$$\langle f, E_{\ell m}^{Rk}\rangle = \cdots$$

$$= \int_0^R w^R{}_{-k}(r) b_{\ell m}(r) dr$$

$$= a_{\ell m}^{Rk}$$

$$f'(r,\theta,\phi) = r f(r,\theta,\phi)$$

H. Skibbe et al.,in Proc. of the 3DIM 2009, part of the 12th IEEE ICCV 2009