

Characterization of 3D fibrous media with geodesic methods

Vincent Morard, Etienne Decencière, Petr Dokládál

Ecole des Mines de Paris
Centre de Morphologie Mathématique

3-D Microstructure Meeting



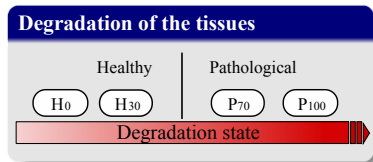
(a)



(b)

Motivations

- 3-D images of biological tissues
- 48 images classify in 2 or 4 classes : $\{\text{Healthy}, \text{Pathological}\}, \{H_0, H_{30}, P_{70}, P_{100}\}$:



Problematic

- Finding relevant features to classify healthy and pathological **fibers**
- Make a statistical analysis

Difficulties

- Anisotropy of the signal
- Small number of images \Rightarrow **overfitting**
- Very high variability between tissues

- 1 Introduction
 - Motivations
 - Pretreatments
- 2 Computation of the features
 - Geodesic methods
 - Skeleton methods
- 3 Statistical analysis
 - Correlation with the degradation
 - Statistical model

Pretreatments

Fibers enhancement

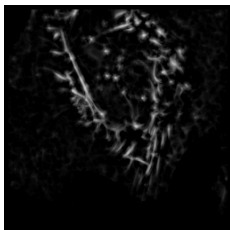
Linear *Difference of Gaussian* (DoG) to detect long structures

→ Image of the fibers in grey scale

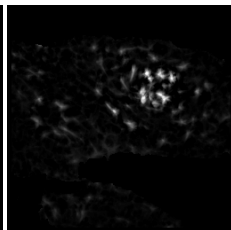
Segmentation of the fibers

No global threshold, then, we use an adaptive threshold for each slice of the 3-D image

→ Mask of the fibers



(c) Healthy tissues H_0

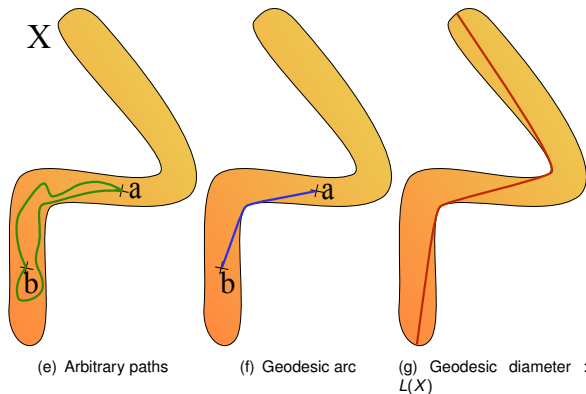


(d) Pathological tissues P_{100}

- 1 Introduction
 - Motivations
 - Pretreatments
- 2 Computation of the features
 - Geodesic methods
 - Skeleton methods
- 3 Statistical analysis
 - Correlation with the degradation
 - Statistical model

Geodesic diameter

Introduced by C. Lantuéjoul in [4].



Geodesy

With the barycentric diameter, we can define other attributes :

- Geodesic elongation

Definition (Geodesic elongation)

in 2D :

$$E(X) = \frac{\pi L^2(X)}{4S(X)}$$

in 3D :

$$E(X) = \frac{\pi L^3(X)}{6V(X)}$$

- Geodesic tortuosity

Definition (Geodesic tortuosity)

$$T(X) = \frac{L(X)}{L_{Eucl}(X)}$$

Geodesic attributes thinnings

The idea is to associate thinnings with geodesic attribute to get a new class of filters (Recently introduced in Morard et al. [5])

$$\psi_{\chi}(X_i) = \begin{cases} X_i & \text{if } \chi(X_i) \text{ is true} \\ \emptyset & \text{otherwise,} \end{cases} \quad (1)$$

Binary thinnings :

$$\rho_{\chi}(X) = \bigcup_i \psi_{\chi}(X_i). \quad (2)$$

Extension to grey scale images

$$\rho^{\circ} f(x) = \vee \{h \in V \mid x \in \rho(X^h(f))\}. \quad (3)$$

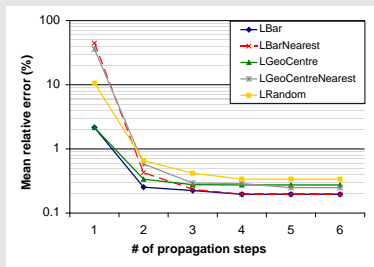
$$\rho^{\top} f(x) = \vee \{h \in V \mid x \in X_j^h : \exists \rho(X_i^k) \neq \emptyset, X_i^k \subseteq X_j^h, \forall k \geq h\}. \quad (4)$$

How to compute efficiently the geodesic diameter ?

Finding an approximation of the geodesic diameter

See Morard et al. [6] : *Efficient geodesic attribute thinnings*

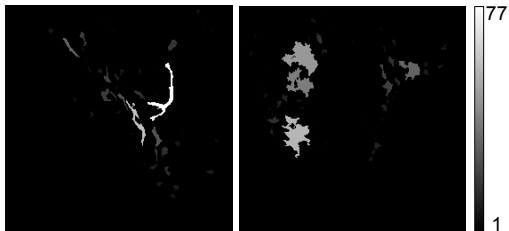
Number of propagation ? Starting point ?



- The starting point is the farthest point from the barycenter of X
- Only 2 propagations

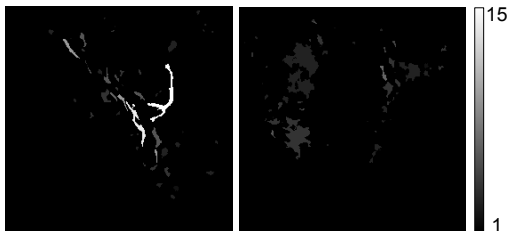
Barycentric diameter

Geodesic methods



(h) Barycentric diameter (Healthy tissues S_0)

(i) Barycentric diameter (Pathological tissues P_{100})

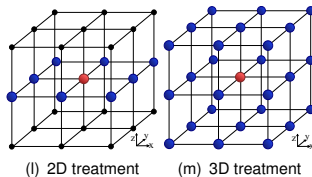


(j) Geodesic elongation (Healthy tissues S_0)

(k) Geodesic Elongation (Pathological tissues P_{100})

Features

We define 2 connectivities $C8$ et $C26$



we get 6 features :

$$F_{L,C,\gamma} = \frac{\text{Card}(\rho_{L>\gamma,C}(f_{FB}))}{\text{Card}(f_{FB})} \times 100$$

$$F_{E,C,\gamma} = \frac{\text{Card}(\rho_{E>\gamma,C}(f_{FB}))}{\text{Card}(f_{FB})} \times 100$$

$$F_{T,C,\gamma} = \frac{\text{Card}(\psi_{T>\gamma,C}(f_{FB}))}{\text{Card}(f_{FB})} \times 100$$

Skeleton of the fibers, spatial features of the fibers

- Computation of the 3D skeleton [1]
- Pruning
- Suppression of the triple points.

We get 3 features :

$$F_{SK_{C_{28},NB}} = \text{CardCC}(f_{Sk,C_{28}})$$

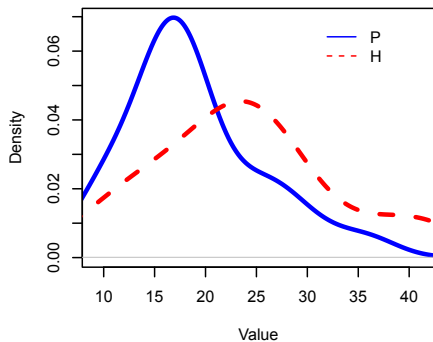
$$F_{SK_{C_{28},MEAN}} = \frac{\sum \text{LengthCC}(f_{Sk,C_{28}})}{F_{SK_{C_{28},NB}}}$$

$$F_{SK_{C_{28},\gamma}} = \text{CardCC}(f_{Sk,C_{28}}) > \gamma$$

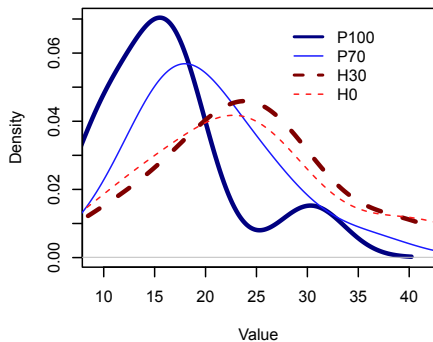
- 1 Introduction
 - Motivations
 - Pretreatments
- 2 Computation of the features
 - Geodesic methods
 - Skeleton methods
- 3 **Statistical analysis**
 - Correlation with the degradation
 - Statistical model

Correlation with the degradation

Elong2D

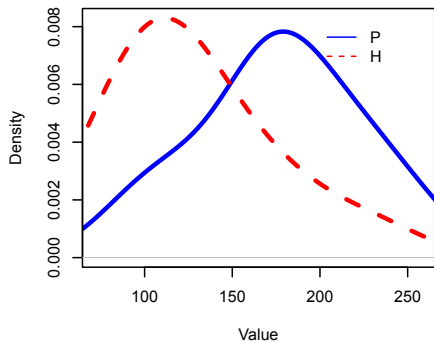


Elong2D

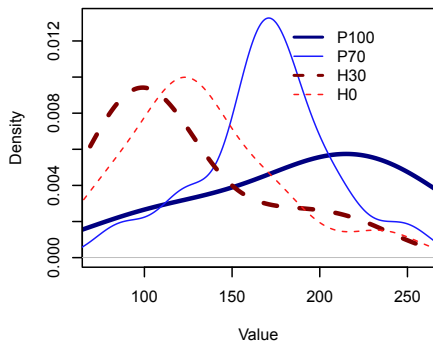


Correlation with the degradation

SK_50



SK_50



Statistical model

To avoid overfitting : → Linear regression

Feature selection :

- LARS, Efron et al. in [2],
- LASSO, Tibshirani in [7],
- Forward Stagewise Selection, Hastie et al. in [3].

Classification

TABLE: Prediction rate and the features are sorted by importance.

	OLS	Stagewise	LASSO	LAR
Prediction Rate	68%	75%	75%	73%
1	$F_{SK,MEAN}$	$F_{SK,MEAN}$	$F_{E,26}$	$F_{E,26}$
2	$F_{E,26}$	$F_{E,26}$	$F_{SK,MEAN}$	$F_{SK,MEAN}$
3	$F_{SK,NB}$	$F_{SK,50}$	$F_{L,26}$	$F_{SK,50}$
4	$F_{T,26}$	$F_{L,26}$	$F_{SK,50}$	$F_{T,8}$
5	$F_{SK,50}$	$F_{T,8}$.	$F_{E,8}$
6	$F_{E,8}$.	.	$F_{L,26}$
7	$F_{L,26}$.	.	.
8	$F_{T,8}$.	.	.
9	$F_{L,8}$.	.	.

Validation method : *Leave One Out*

Conclusion

- Characterization of the fibers with geodesic methods
- A new attribute is introduced to speed up the computation : the barycentric diameter
- Characterization of the structures with the skeleton
- Statistical analysis with a *subset selection*

 P. Dokladal, C. Lohou, L. Perroton, and G. Bertrand.

A new thinning algorithm and its application to extraction of blood vessels, 1999.

 B. Efron, T. Hastie, I. Johnstone, and R. Tibshirani.

Least angle regression.

Annals of statistics, 32(2) :407–451, 2004.

 T. Hastie, R. Tibshirani, and J. Friedman.

The elements of statistical learning : data mining, inference, and prediction. volume2.
Springer Verlag, 2009.

 C. Lantuejoul and S. Beucher.

Geodesic distance and image analysis.

pages 138–142, Salzburg, Australia, 1980. *Mikroskopie*.

 V. Morard, E. Decencière, and P. Dokládál.

Geodesic attributes thinnings and thickenings.

In *International Symposium on Mathematical Morphology*. Springer, 2011.

 V. Morard, E. Decencière, and P. Dokládál.

Efficient geodesic attribute thinnings (submitted).

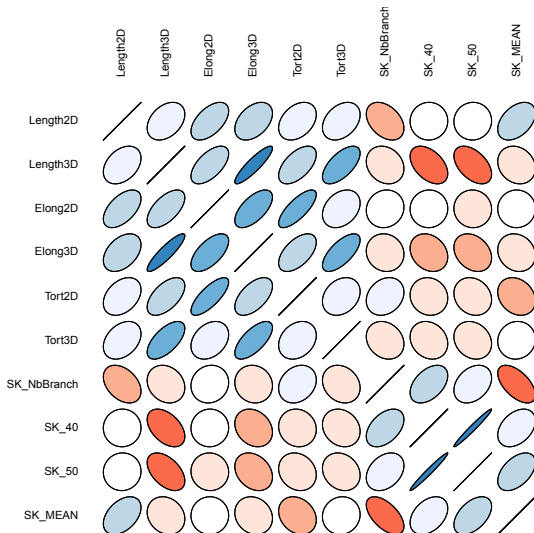
Journal of Mathematical Images and Vision, 2011.

 R. Tibshirani.

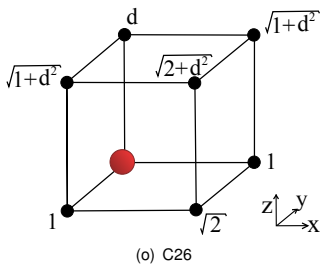
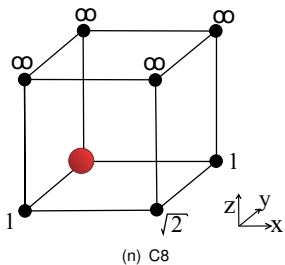
Regression shrinkage and selection via the lasso.

Journal of the Royal Statistical Society. Series B (Methodological), pages 267–288, 1996.

Annexe 1 : Correlation matrices



Annexe 2 : Anisotropy of the signal



Annexe 3 : Binary objects



(a) Convex



(c) Ball aggregation



(b) Pixel aggregation



(d) Random walk

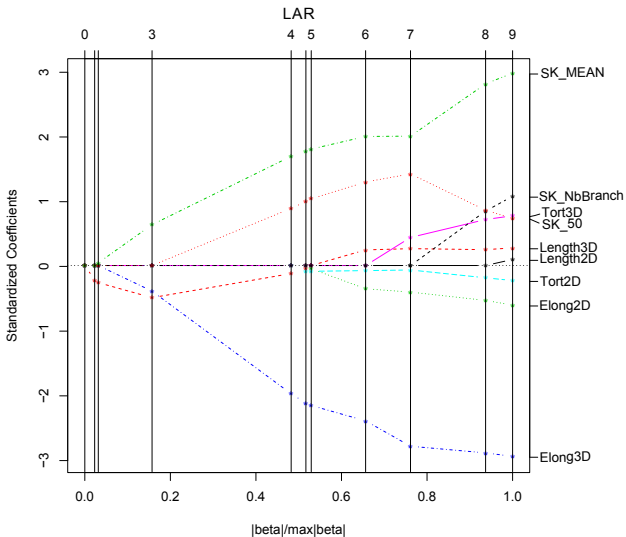


(e) Perlin Noise

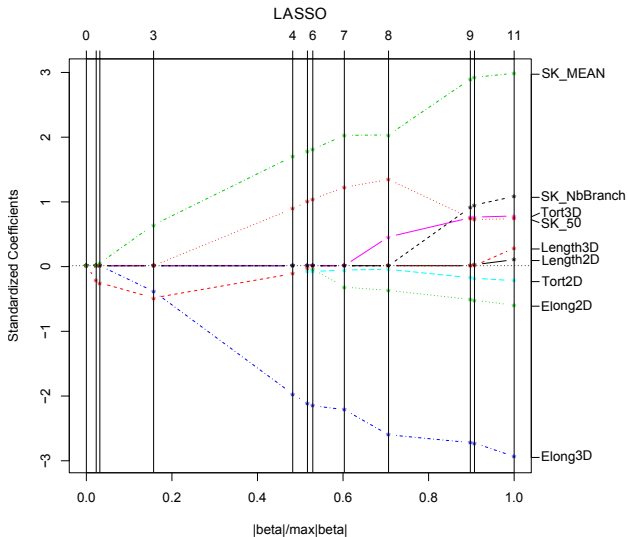


(e) Data base MPEG7

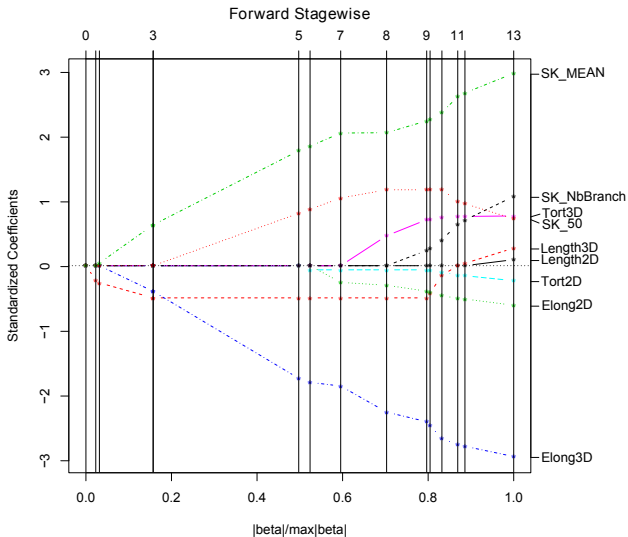
Annexe 4 : Regularization path LARS



Annexe 5 : Regularization path LASSO



Annexe 6 : Regularization path Forward stagewise selection



Annexe 7 : Correlation with the degradation

