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Statistical models of the spine with applications in medical image processing

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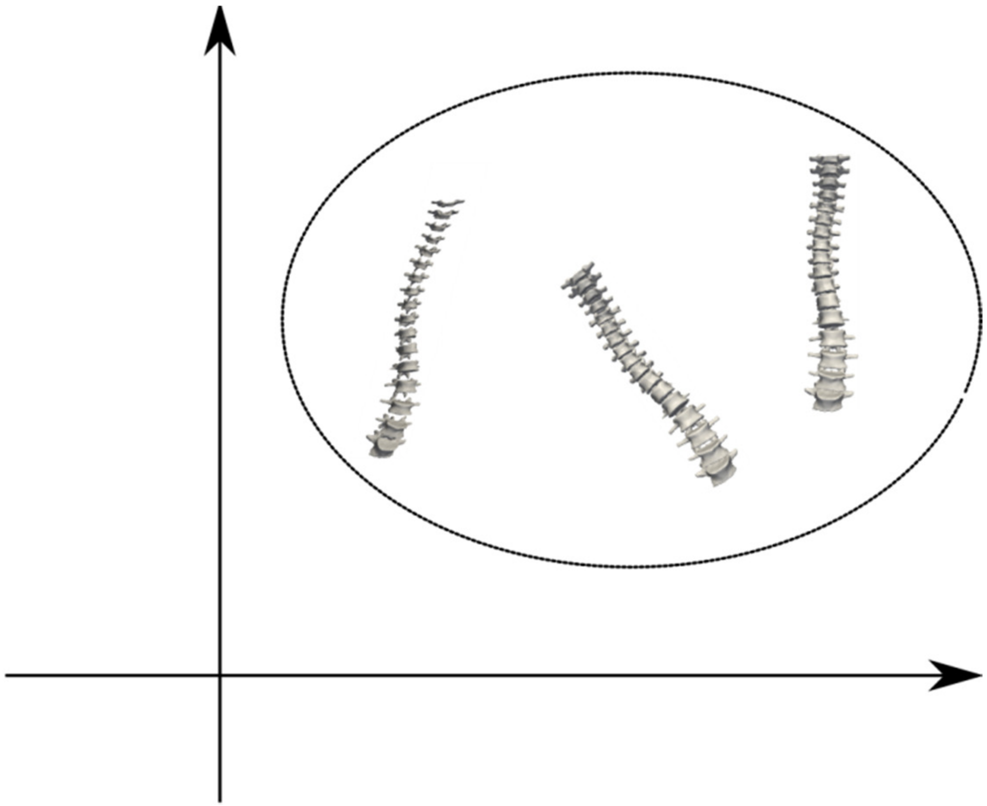
POLYTECH MONS

A Statistical Model?

Sub-space characterizing a variable X based on observations



Relevant informations about the model

- Statistical limits of the sub-space
- Mean of the sample
- How does evolve X inside the sub-space?

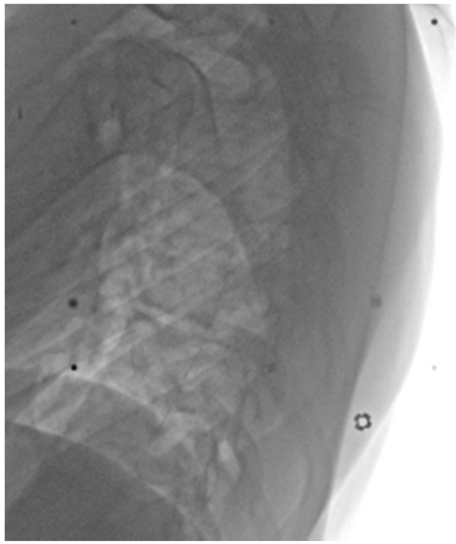
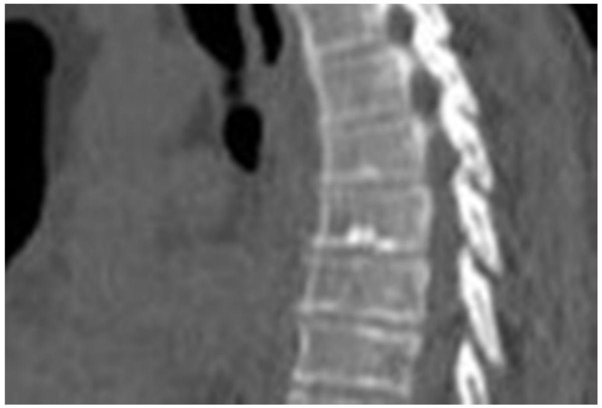
Conventional Radiography

Advantages

- Relatively weak exposure to radiation
- Fast and not expensive → widely used in ER

Disadvantages

- Human body only in 2D (not always a disadvantage)
- Poor quality

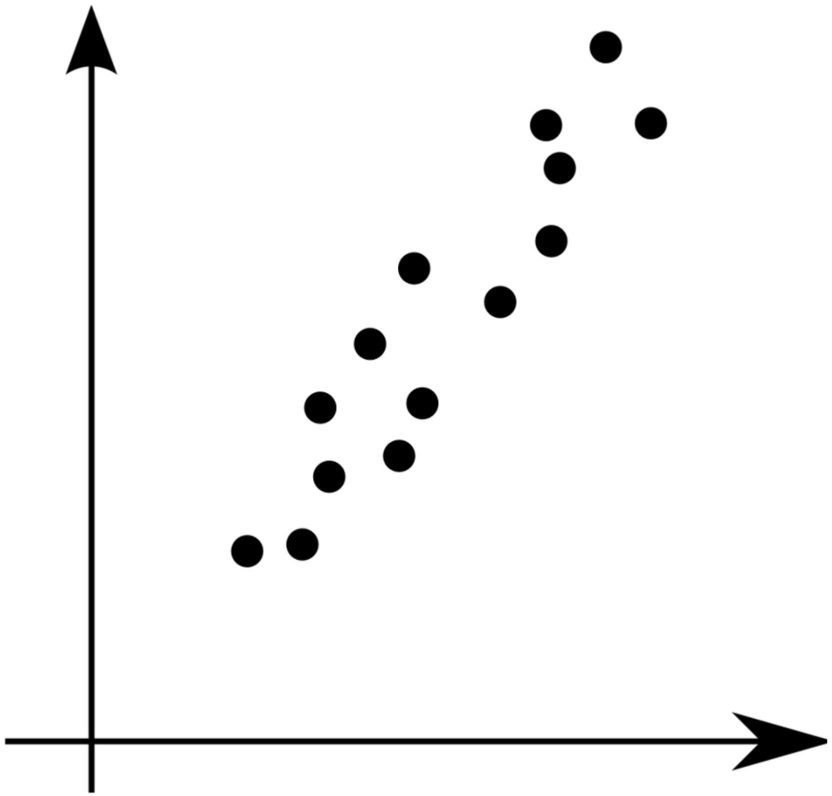




Objectives of my thesis

- Statistical models can help to deal with poor quality images
- Application to the analysis of the spine on radiographs
- We'll see how to extract 2D or 3D spine shapes to compute clinical indices

Statistical model defined by PCA

$$x = \bar{x} + \phi d$$



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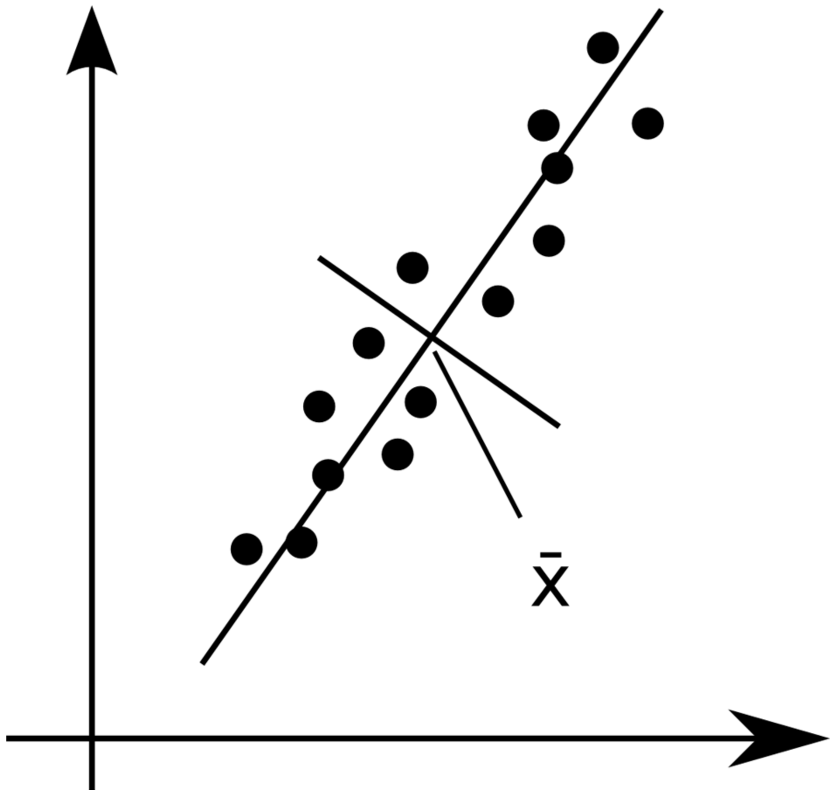
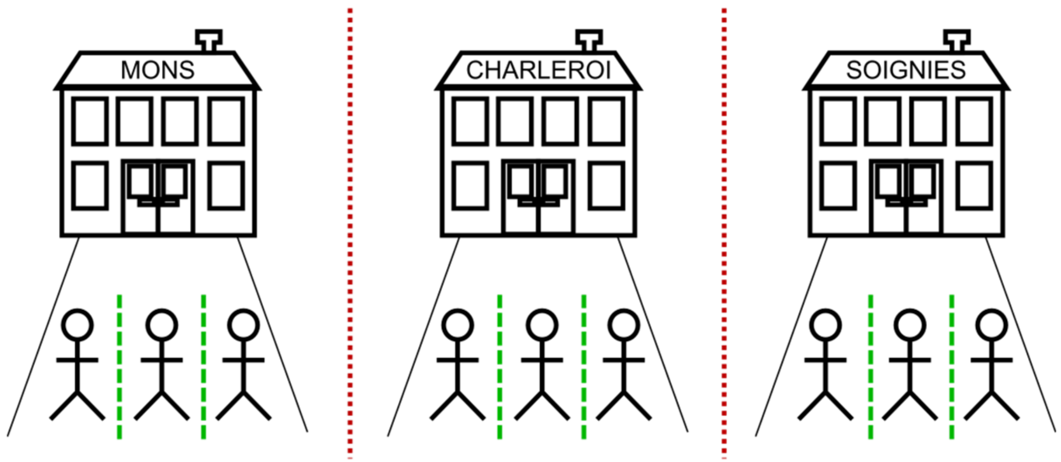


Presentation Overview

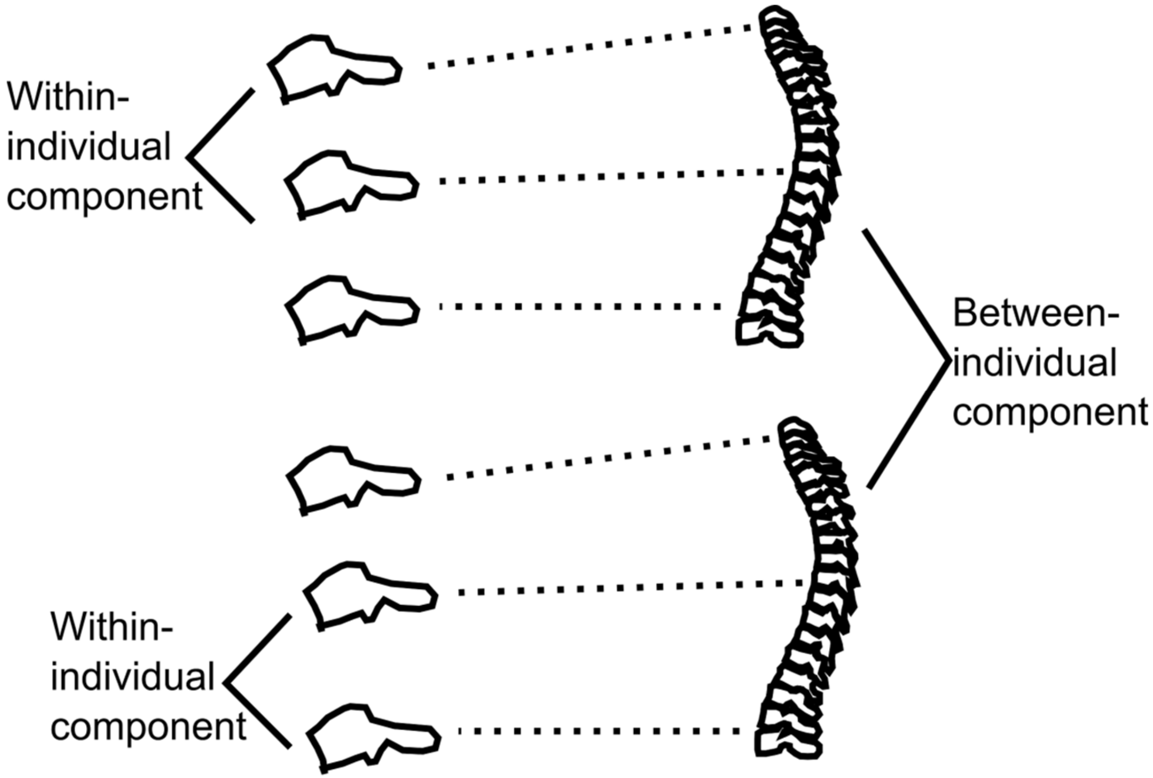
What if the shape has a hierarchical structure?

- In biomedical applications, data can have a hierarchical structure
- Usual models do not represent the link existing between the items of a structure

Example: evaluating school performance of students



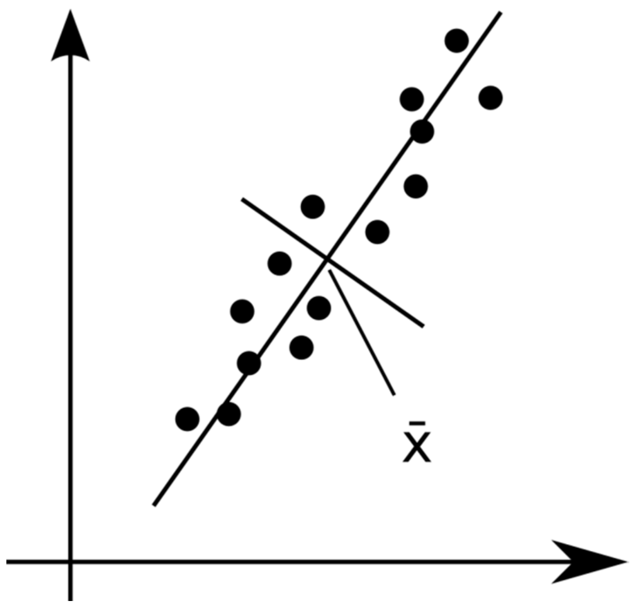
Multilevel Model

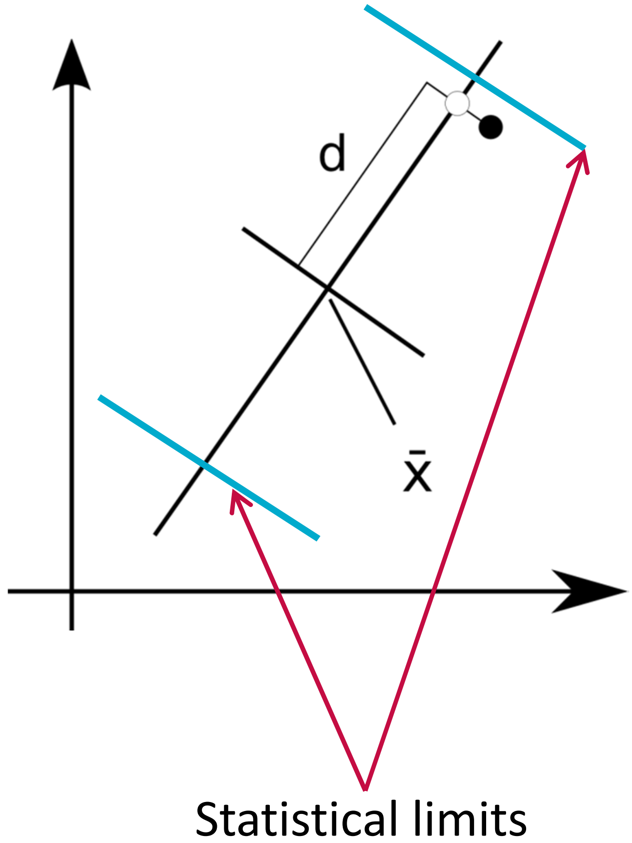


$$\boxed{x_i = \bar{x} + \sum_{l=1}^{L-1} \phi_{W_{l},i} d_{W_l} + \phi_B d_B}$$

→Global representation of the spine

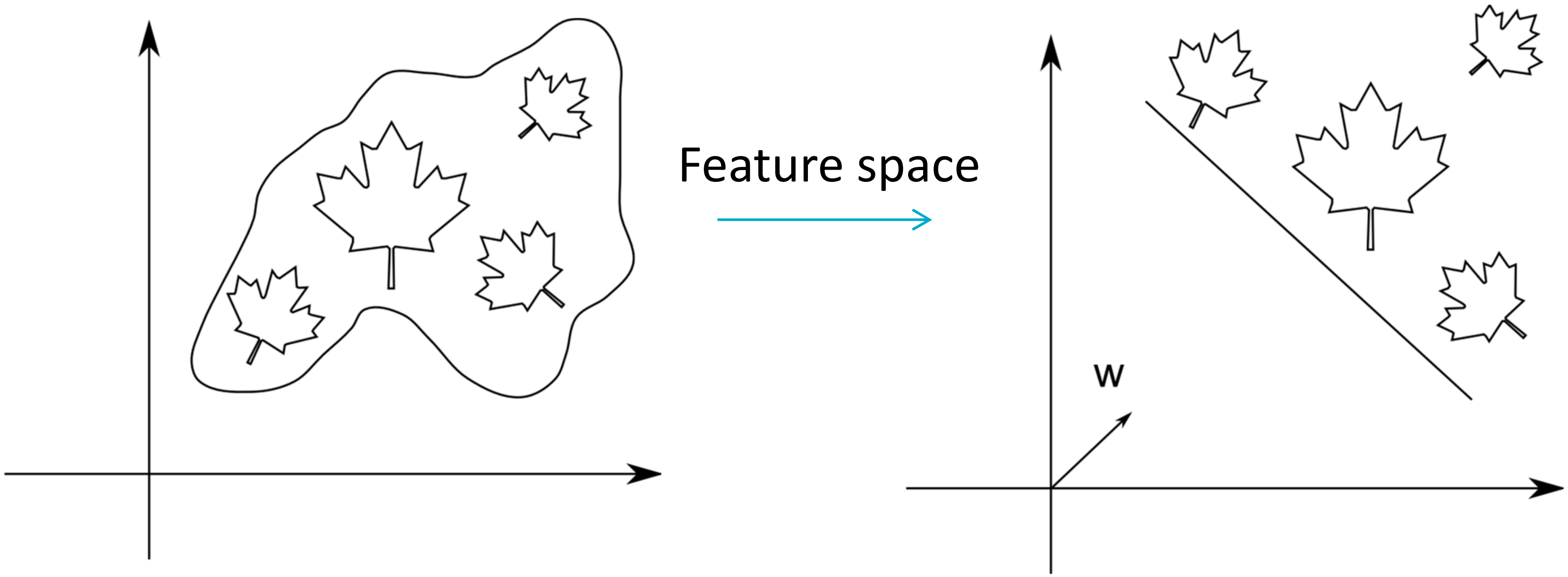
These models are defined by statistical hypothesis





Shape modeling based on data separation

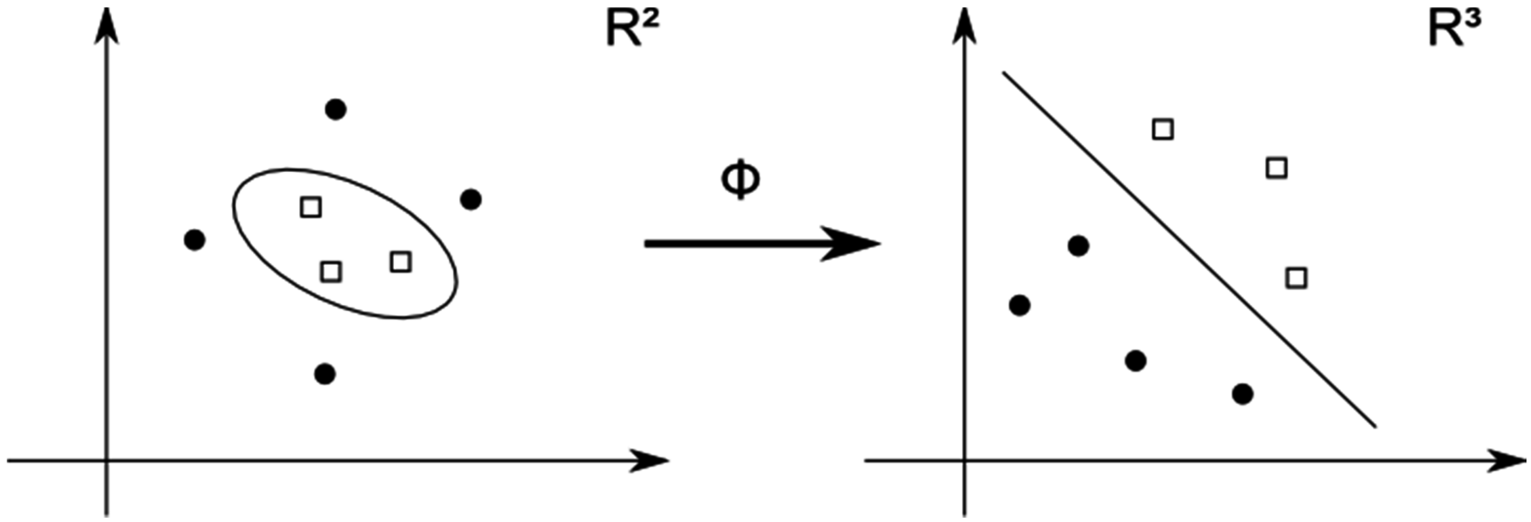
- A shape is modelized given an hyperplane representing a class of data :



- Machine learning method: One-Class Support Vector Machine (OCSVM)

Separation defined with a kernel

- The hyperplane is computed from a kernel function



- Only the inner product $\mathrm{k}(\mathrm{x}, \mathrm{x_i}) = \langle \Phi(x), \Phi(x_i) \rangle$ is required

- $\mathrm{k}(\mathrm{x}, \mathrm{x_i})$: easy to define but not easy to choose !

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I. Models
- Multilevel statistical shape model
- Machine learning-based model

II. **Vertebral Mobility**
- **Context**
- **Automatic vertebra detection**
- **Vertebra segmentation**

III. Scoliosis
- Context
- 3D reconstruction with a statistical shape model
- 3D reconstruction with a machine learning-based model

IV. Conclusion

Vertebral Mobility

Measuring the vertebra orientations in different positions



Mobility Analysis: a Fully Automatic Approach

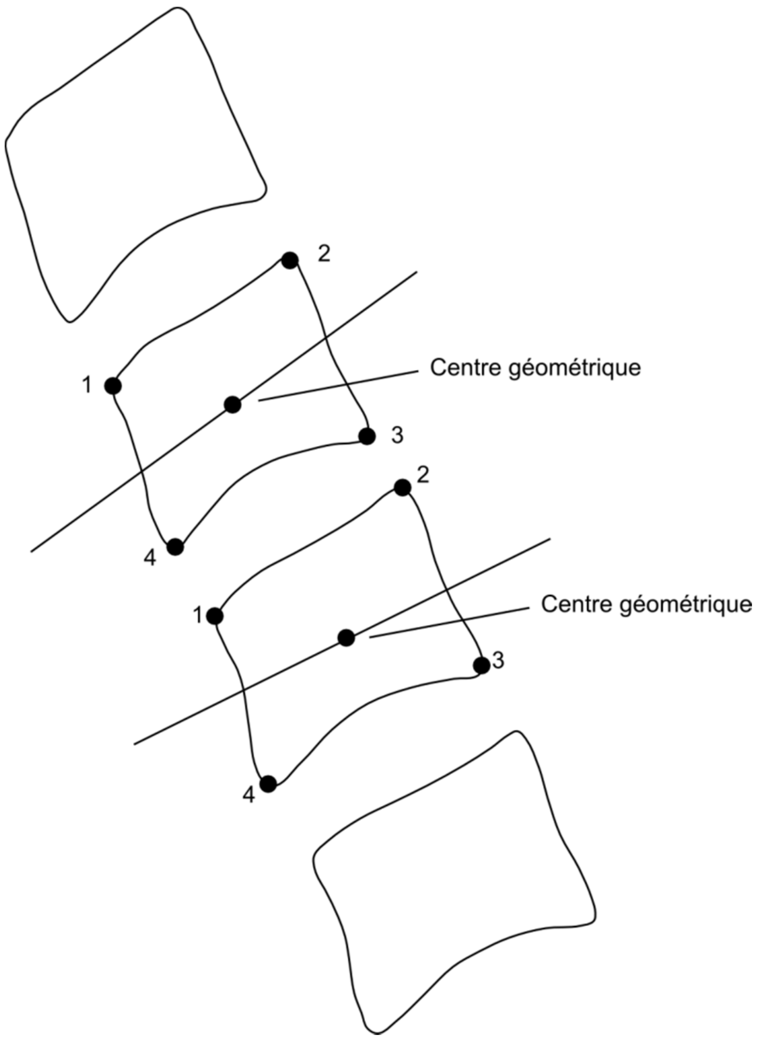
Why is the mobility important?

- Helpful for diagnosis of vertebral pains (ex: trauma)
- Some pathologies imply a decrease of mobility → need to quantify

Why a fully automatic approach?

- Quickly providing quantitative data
- No inter-operator variability
- Processing lots of images (ex: for medical research)

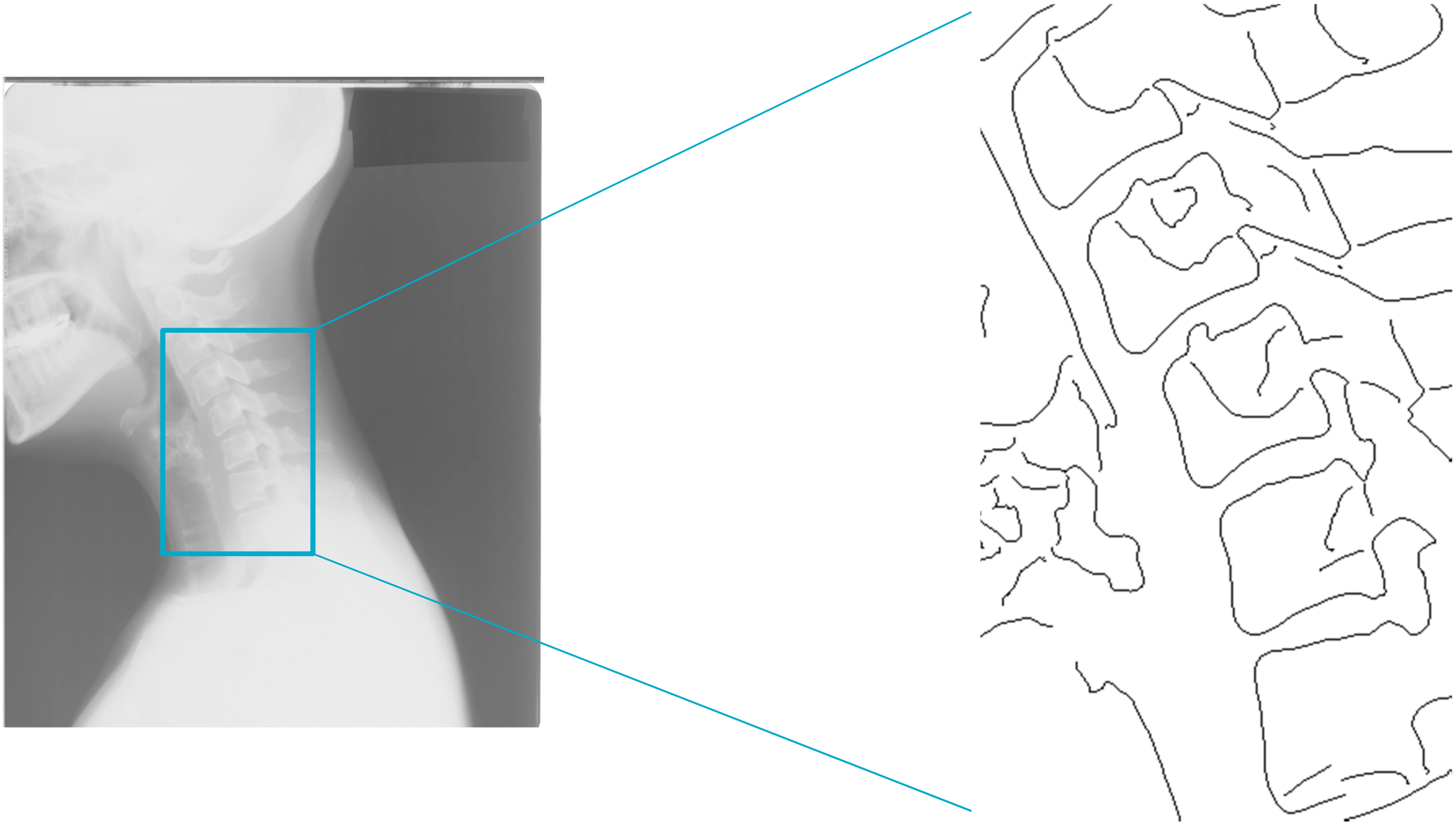
Measuring Protocol



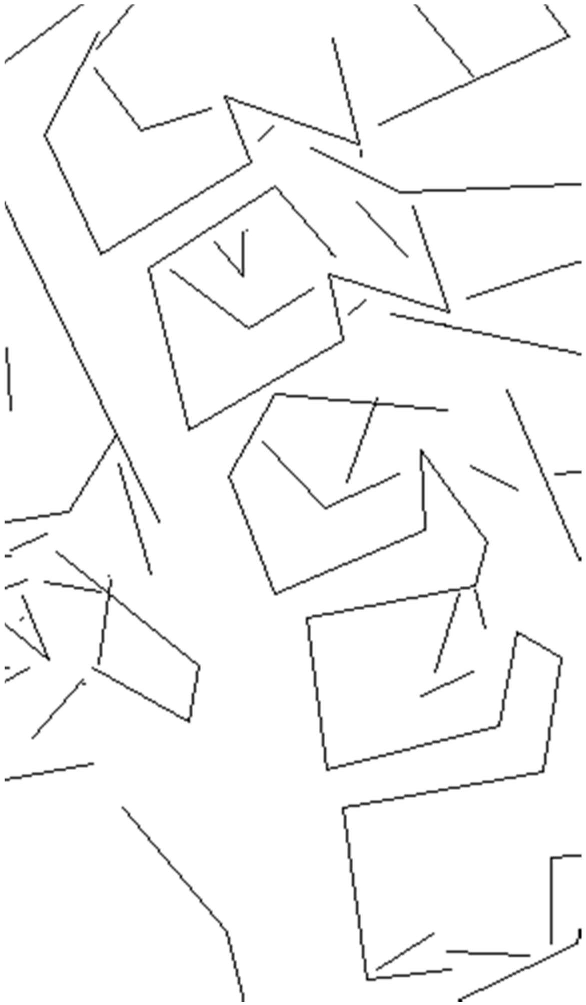
Framework in Three Steps

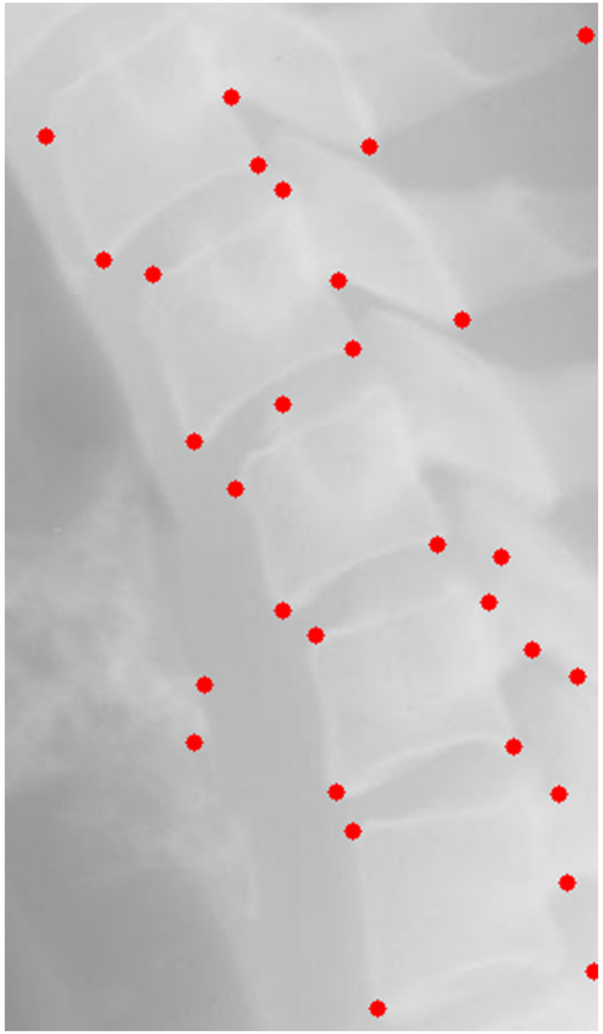
Vertebra Detection → Vertebra Segmentation → Mobility Analysis

Canny Edge Detector

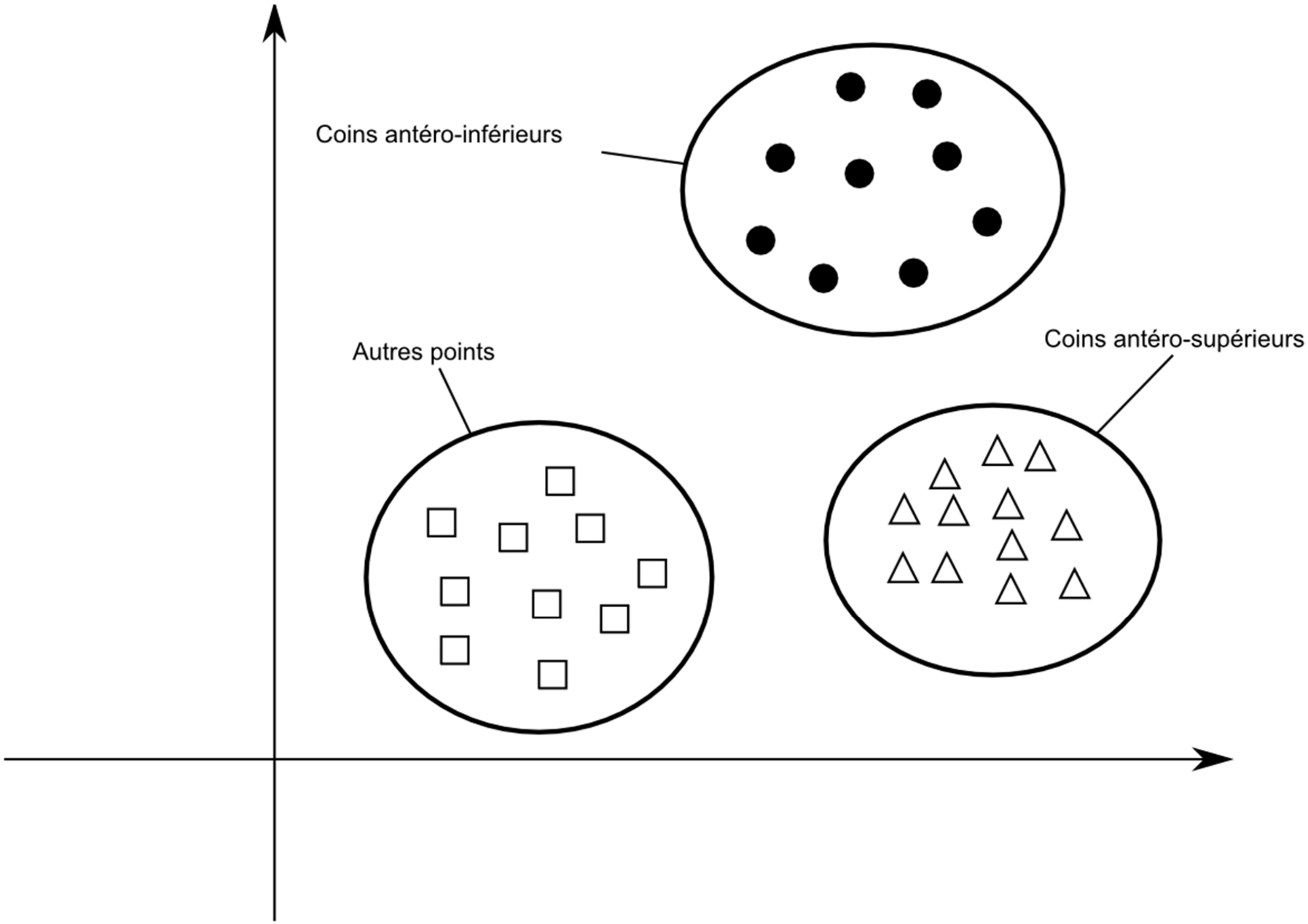


Geometrical Definition of a Corner



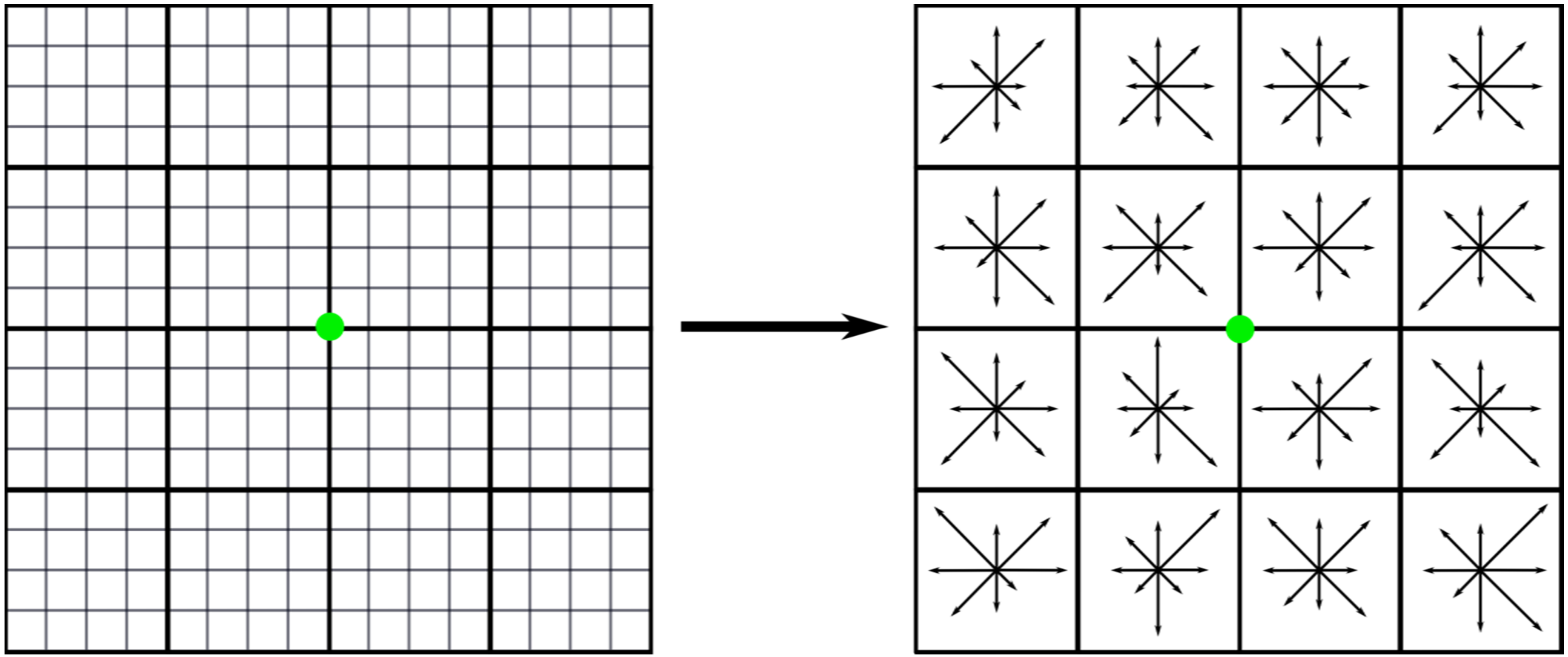


Support Vector Machine



Interest Point Description

- Descriptor: features about the module and the orientation of the gradient



Descriptors: SIFT and SURF

SIFT Descriptor

- 128 features
- Invariant to scale, rotation and illumination
- Fast

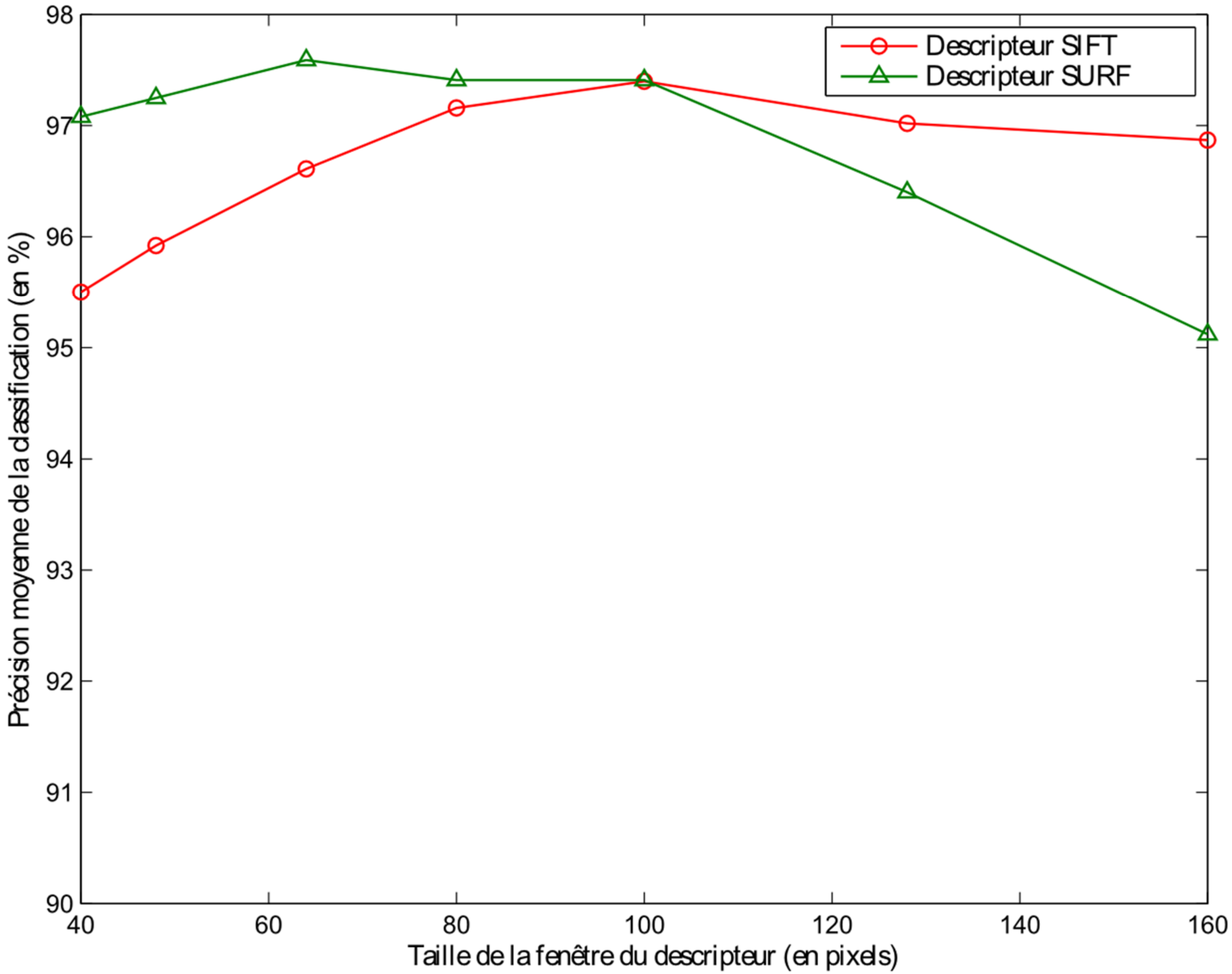
SURF Descriptor

- 64 features
- Invariant to scale and rotation
- Very fast

Experiments

- 49 radiographs : cervical vertebrae C3 to C7
- *leave-one-out* cross-validation
- Corner and vertebra detection rates
- Precision of classification
- Results depend on a parameter: window descriptor size

Experiments



Experiments

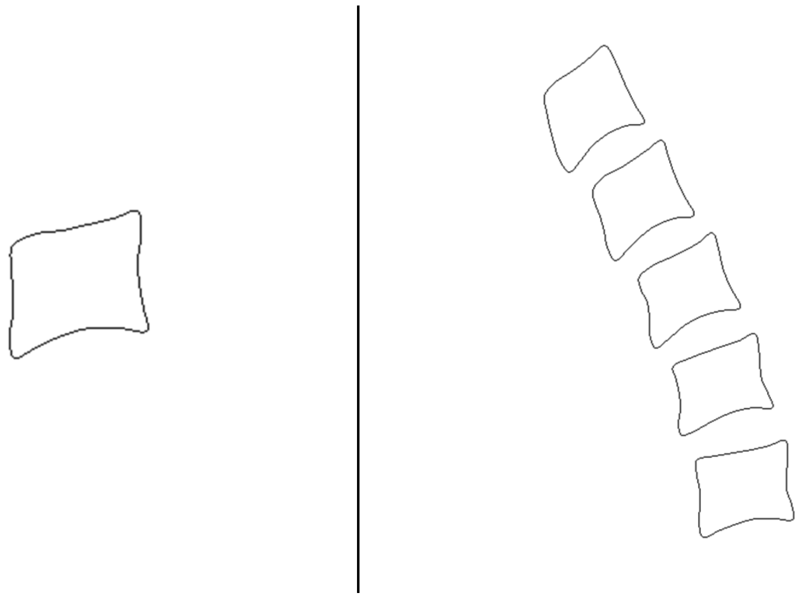
Type de vertèbre	Type de coin	Taux de détection	
C3	Sup.	93,3%	91,3%
	Inf.	93,3%	
C4	Sup.	97,8%	95,7%
	Inf.	100,0%	
C5	Sup.	100,0%	95,6%
	Inf.	97,7%	
C6	Sup.	95,4%	93,3%
	Inf.	97,7%	
C7	Sup.	75,0%	72,9%
	Inf.	75,0%	
Moyenne		92,5%	89,8%

TABLE 1.19: Taux de détection des coins et des vertèbres : SURF - Taille de fenêtre = 64 (avec application de la récupération des points non-détectés)

Active Shape Model

- Statistical Shape Model

$$x = \bar{x} + \phi d$$



- Model of grey level variation around the shape

Initialization close to the object

- Mean shape is placed near the detected vertebrae

The Model is Deformable

- The texture in the neighborhood of the landmarks is analyzed

Vertebral Mobility: Conclusion

- Inter-operator variability on radiographs: 3,14°
- Our approach vs. expert landmarking: between 3,15° and 3,36°

→ Our approach is as precise as a group of radiologists

- Limitation: all the process relies on the good detection of the edges

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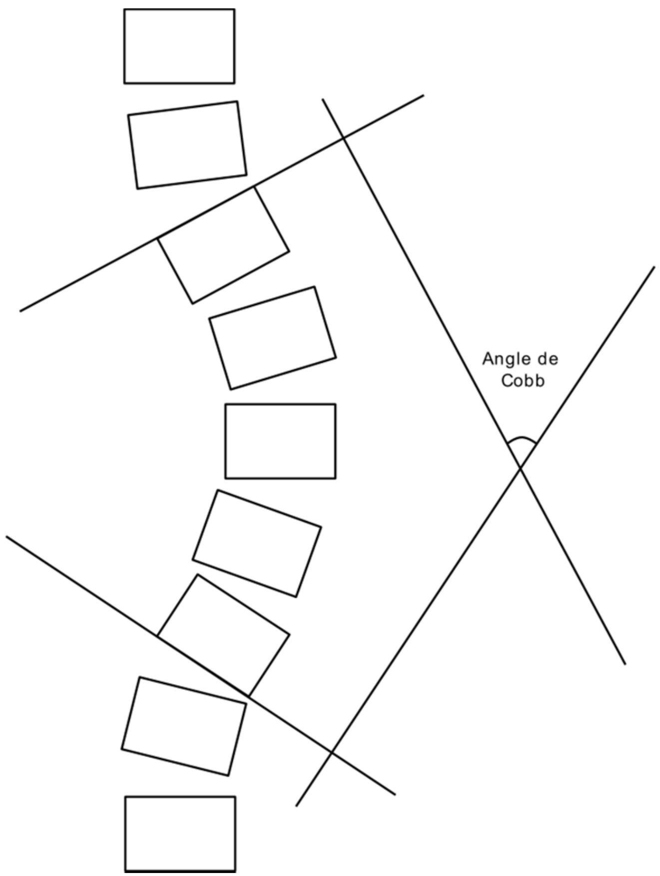
3D Deformation Represented with a 2D Clinical Measure

Cobb angle: widely used



The interest of 3D clinical indices has been shown in the literature

Reconstructing the Spine from Radiographs

Why using radiographs?

- Fast and not expensive
- CT-Scan: important exposure, lying position
- MRI: expensive, lying position

→ Disadvantage: weak image quality, poor contrast

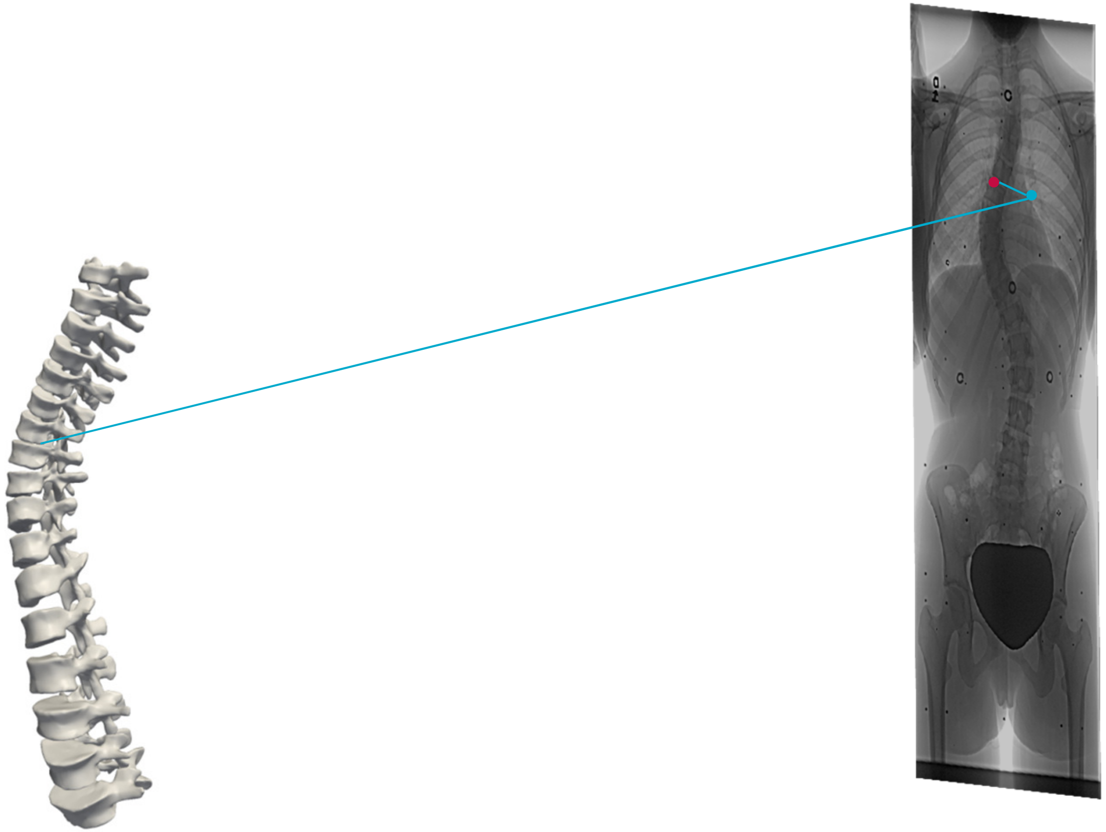
What for?

- Scoliosis diagnosis
- Personalized Treatments
- Surgery planning

General Principle

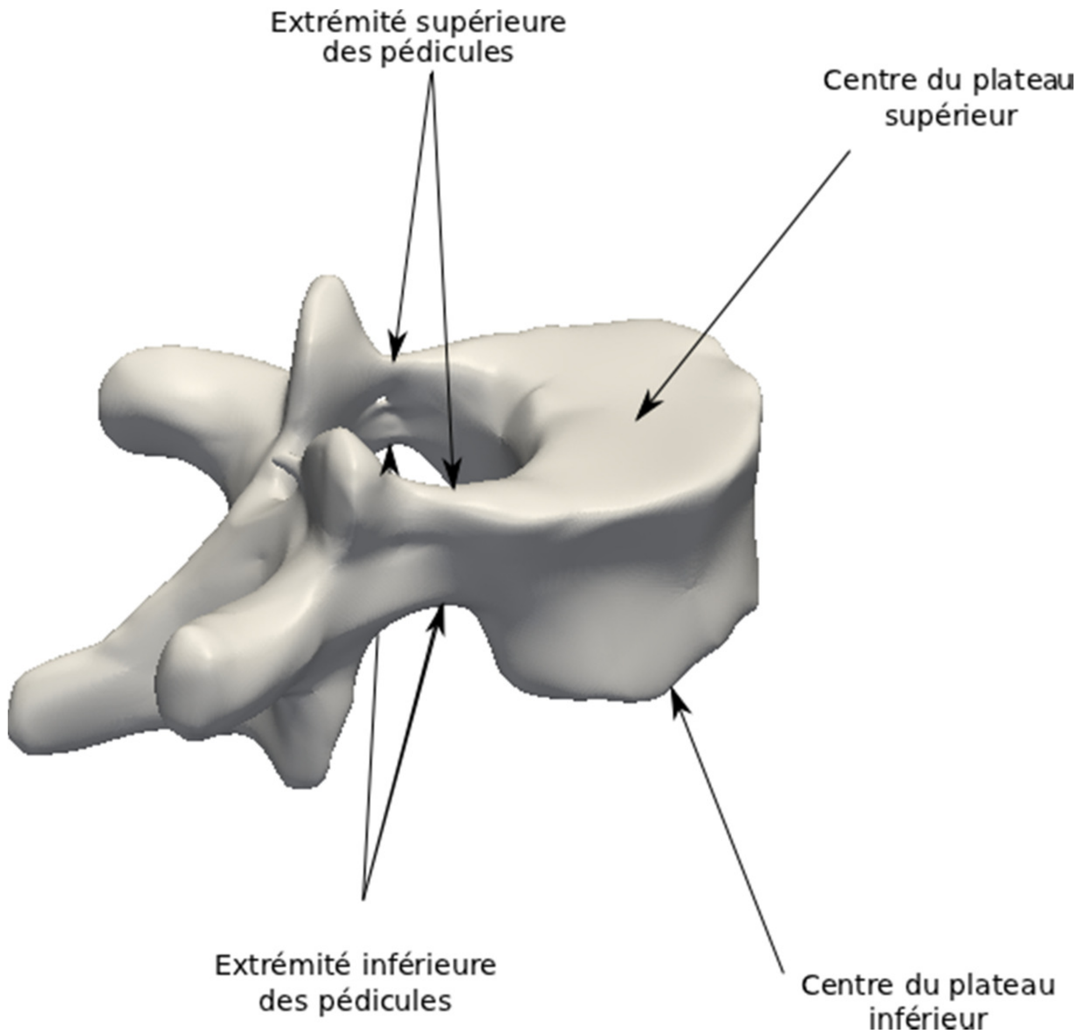
Optimization of two measures:

- Reprojection error



- Similarity of the deformed shape with the statistical model

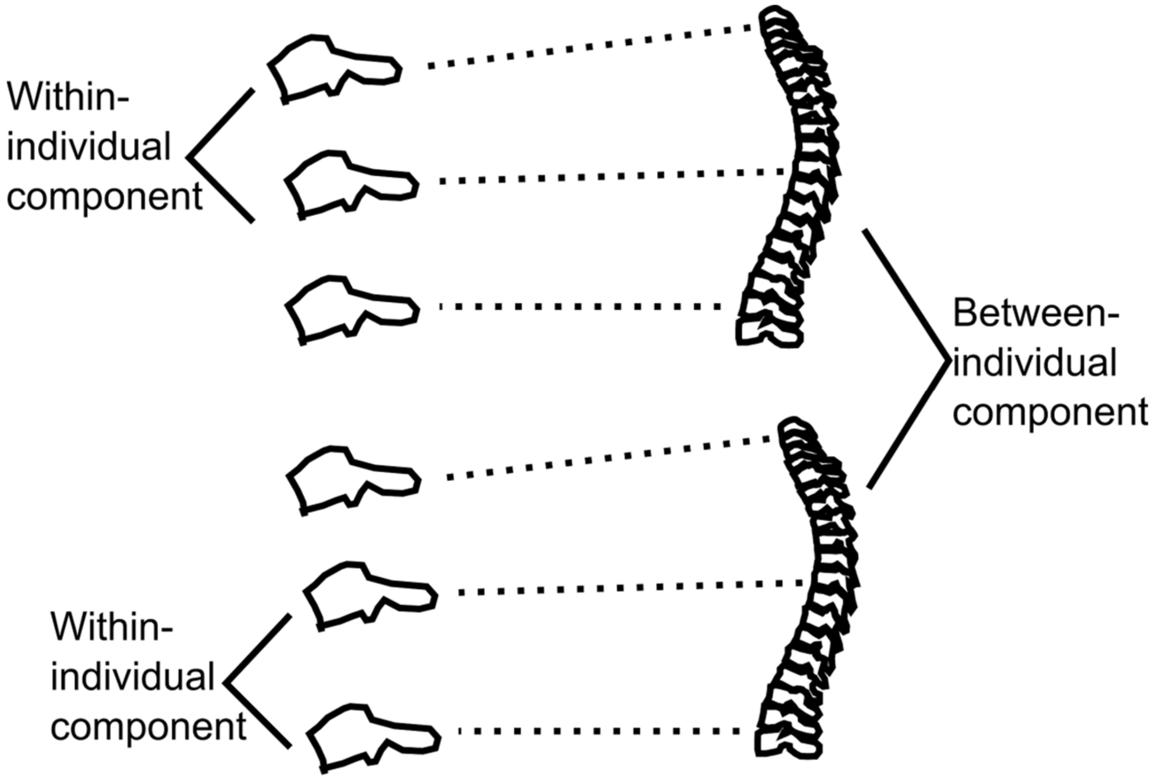
3D Representation with Anatomical Landmarks



Statistical Shape Model

$$x = \bar{x} + \phi d$$

Multilevel Model

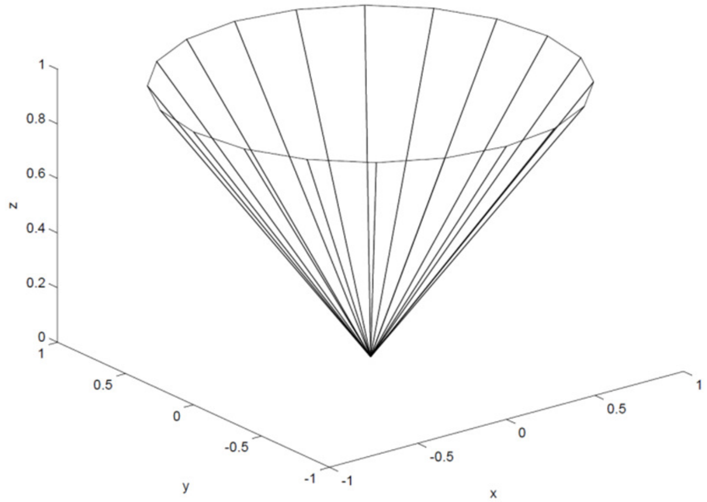


$$x_i = \bar{x} + \sum_{l=1}^{L-1} \phi_{W_l,i} d_{W_l} + \phi_B d_B$$

Convex Optimization

SOCP (Second Order Cone Programming) formulation:

$$\begin{cases} \min & f(x) \\ s.c. & \|A_i x + b_i\|_2 - (c_i^T x + d_i) \leq 0 \quad i = 1, \ldots, m \end{cases}$$



Advantage: the solution is found very quickly

$$\begin{cases} \min & t \\ s.c. & \left\| \Sigma^{-1/2} (X - \bar{X}) \right\|_2 \leq t, \\ & \left\| \begin{pmatrix} P_1^j - P_3^j u_{k,x}^j \\ P_2^j - P_3^j u_{k,y}^j \end{pmatrix} \begin{pmatrix} X_k \\ 1 \end{pmatrix} \right\|_2 \leq \gamma_{max} P_3^j \begin{pmatrix} X_k \\ 1 \end{pmatrix} \end{cases}$$

Very Fast Solving

$$\begin{cases} \min & t \\ s.c. & \left\| \Sigma^{-1/2} (X - \bar{X}) \right\|_2 \leq t, \\ & \left\| \begin{pmatrix} P_1^j - P_3^j u_{k,x}^j \\ P_2^j - P_3^j u_{k,y}^j \end{pmatrix} \begin{pmatrix} X_k \\ 1 \end{pmatrix} \right\|_2 \leq \gamma_{max} P_3^j \begin{pmatrix} X_k \\ 1 \end{pmatrix} \end{cases}$$

Statistical Shape Model

$$\boxed{x = \bar{x} + \phi d}$$

Multilevel Statistical Shape Model

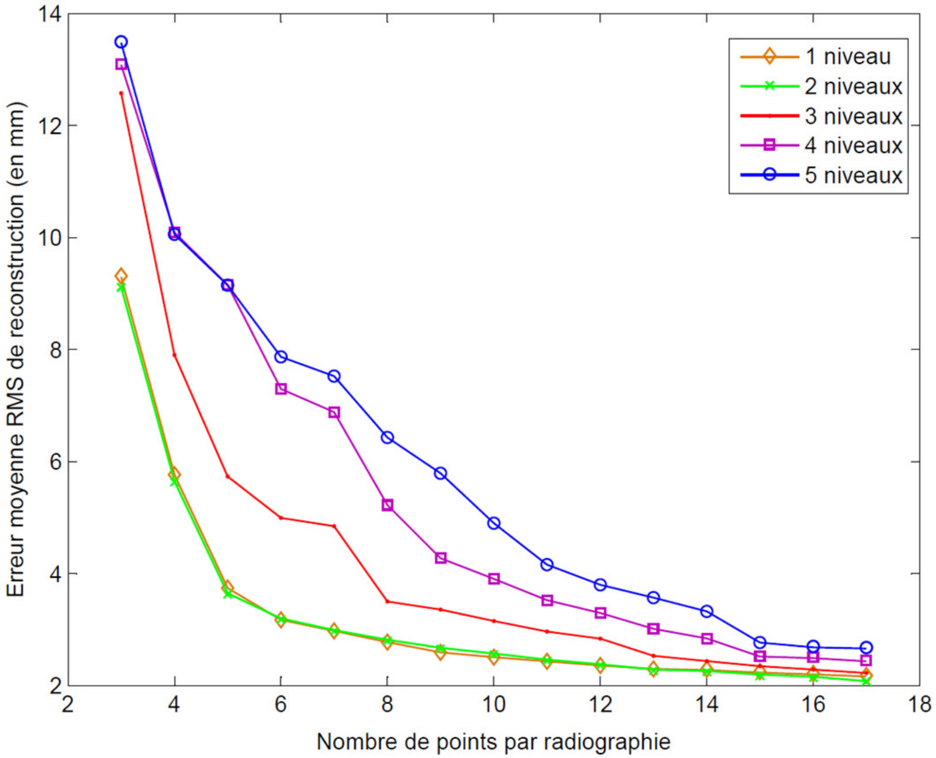
$$\boxed{x_i = \bar{x} + \sum_{l=1}^{L-1} \phi_{W_l,i} d_{W_l} + \phi_B d_B}$$

Experiments

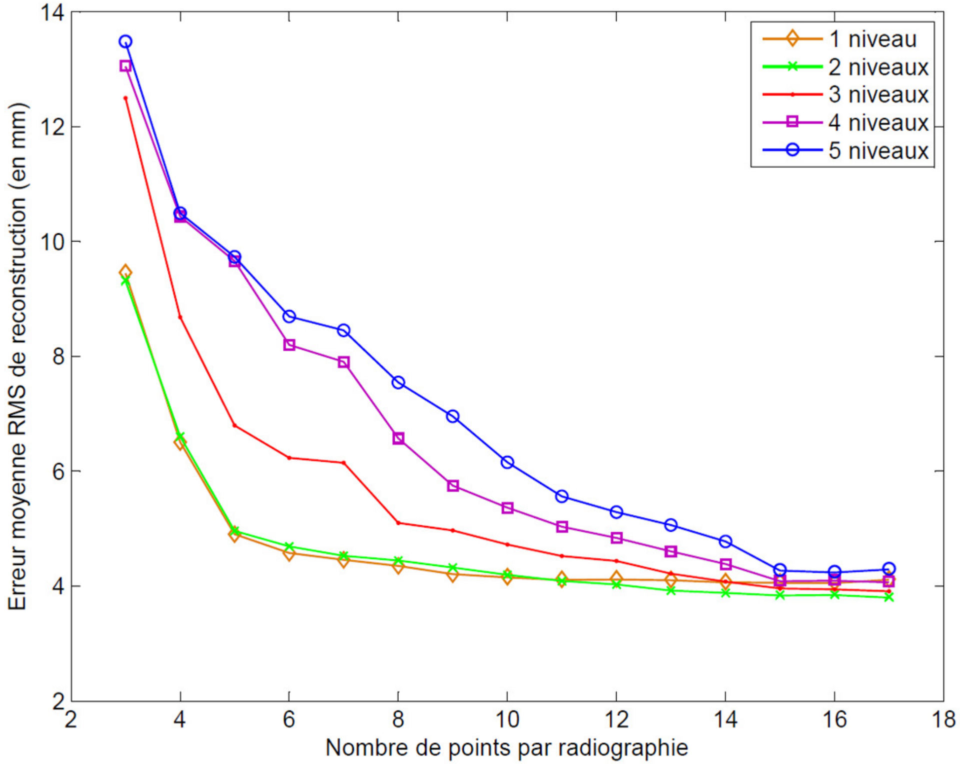
- 20 severe cases: Cobb angle between 44° and 70° (Sainte-Justine Hospital, Montréal)
- 25 cases with surgical instrumentation → presence of discontinuities in the spine
- 17 vertebrae are reconstructed: T1 to L5
- Reconstruction error: euclidean distance to a reference 3D model
- Reconstruction time

Experiments

Reconstruction Error



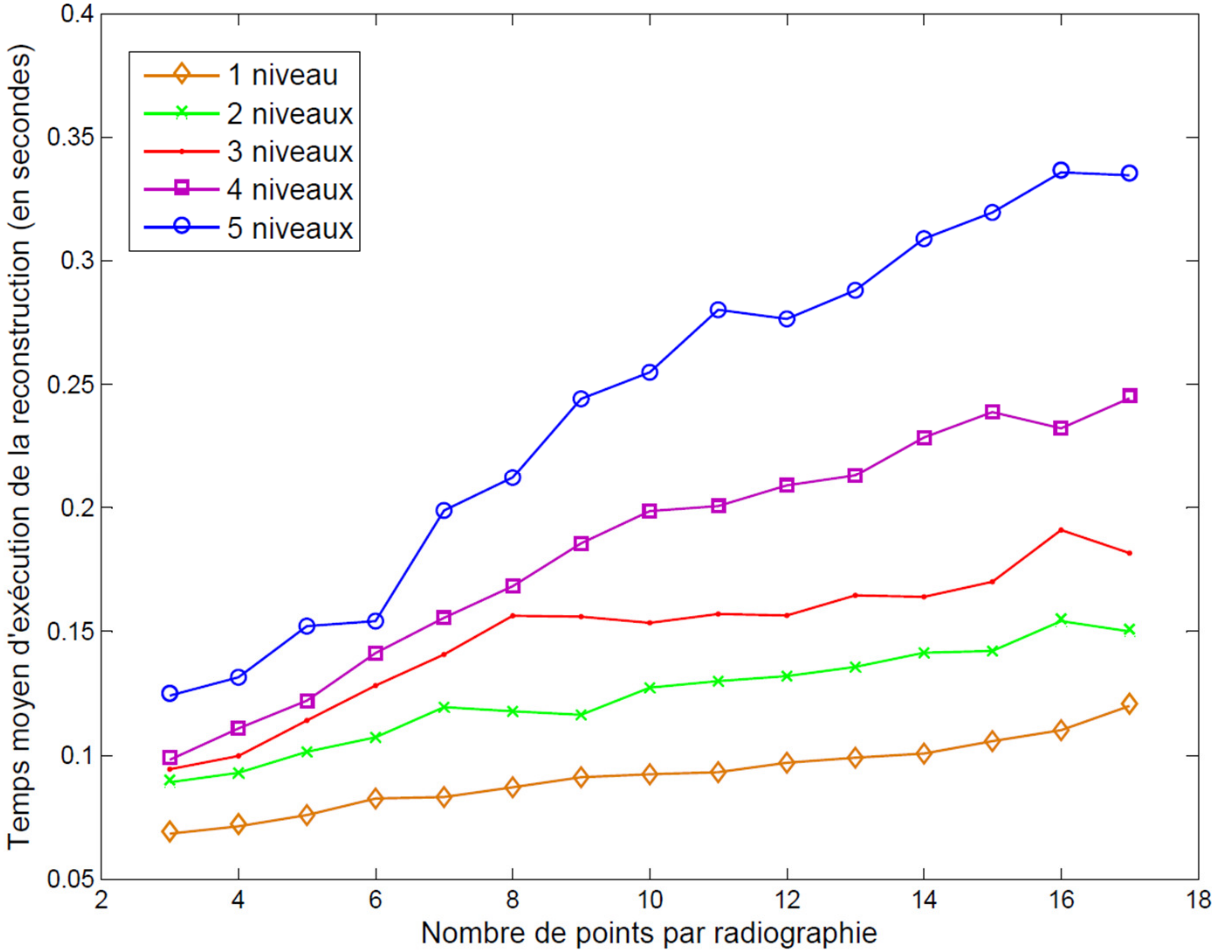
Plates



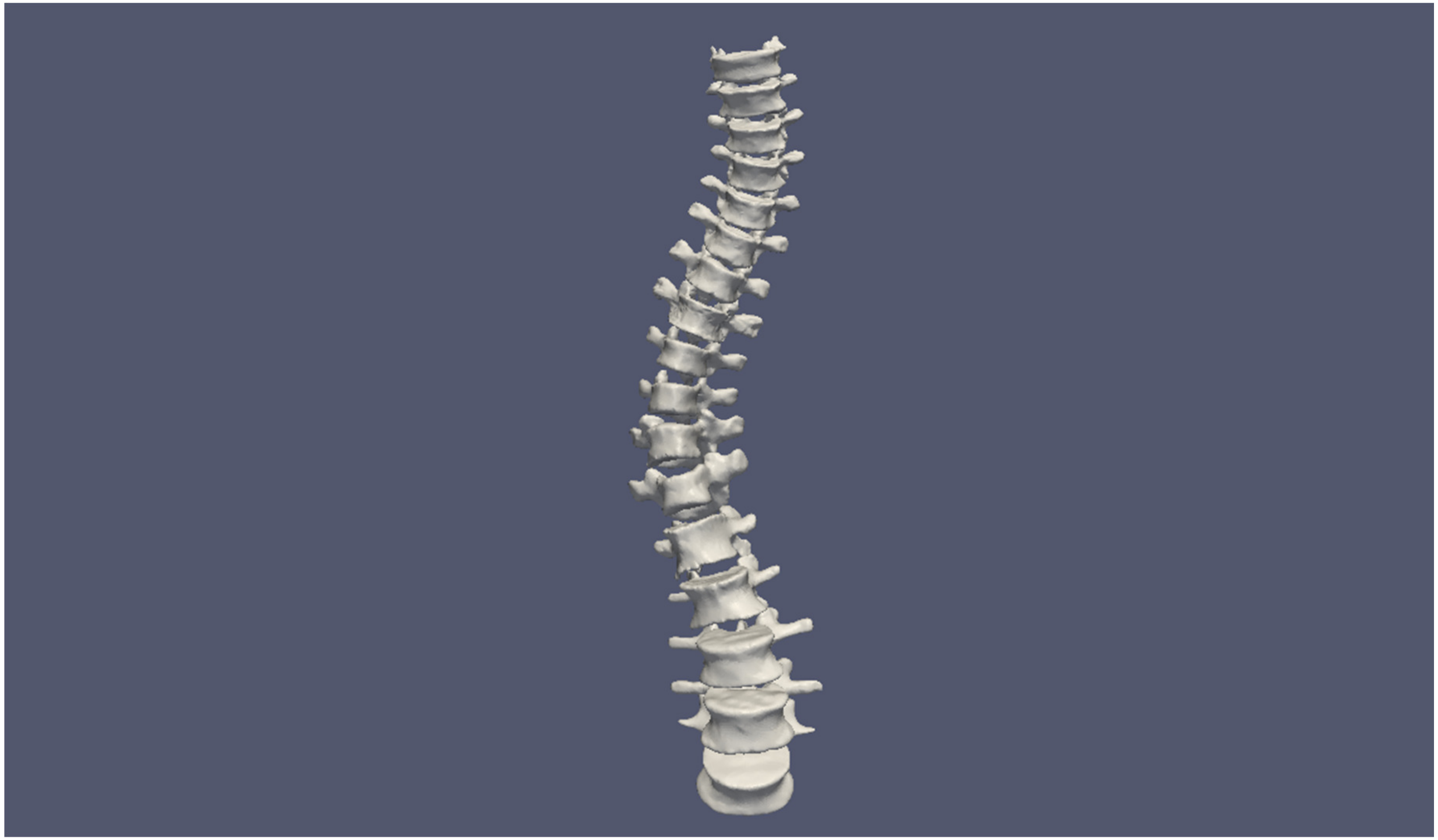
Pedicles

Experiments

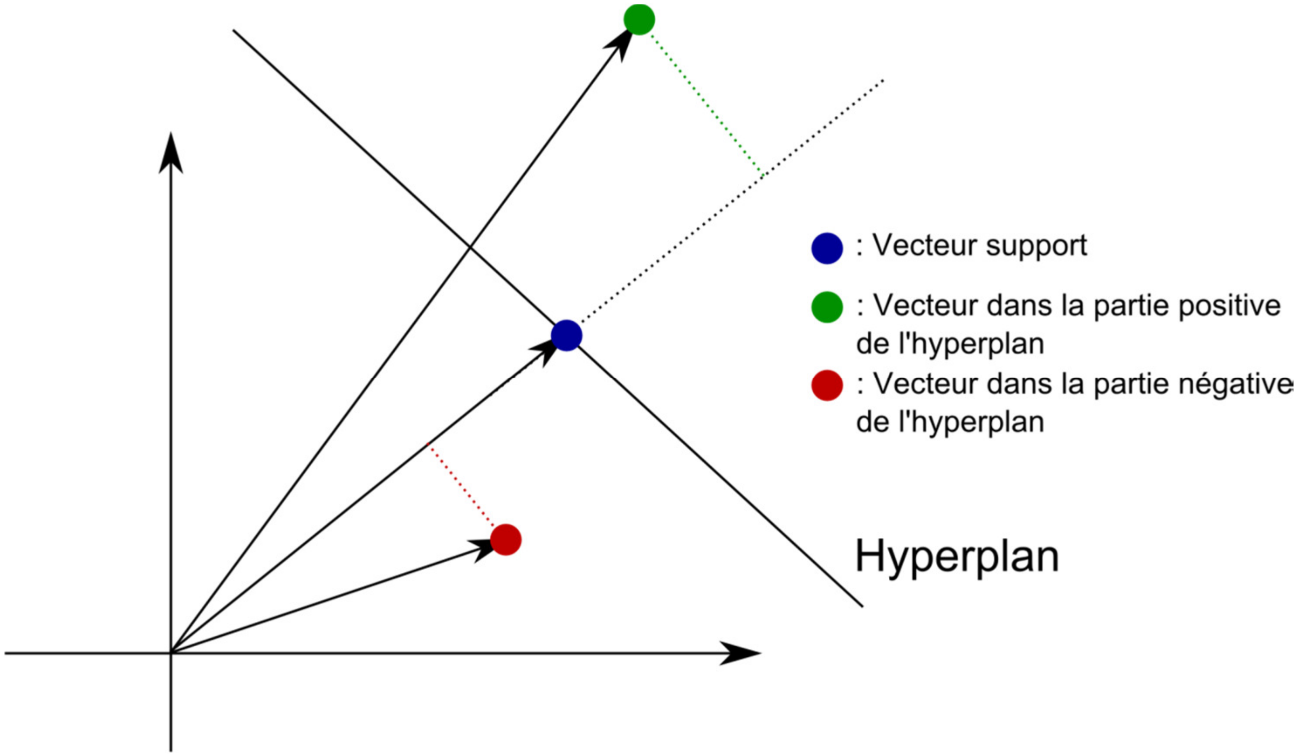
Time of reconstruction



Experiments



One-Class SVM for 3D Reconstruction



Reconstruction algorithm based on the minimization of two measures:

$$f = \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1}^{K} \left\| p_{i,j,k}^{2D} - \tilde{p}_{i,j,k}^{2D} \right\|_2^2 + \beta \left(\frac{1}{s} \right)^2$$

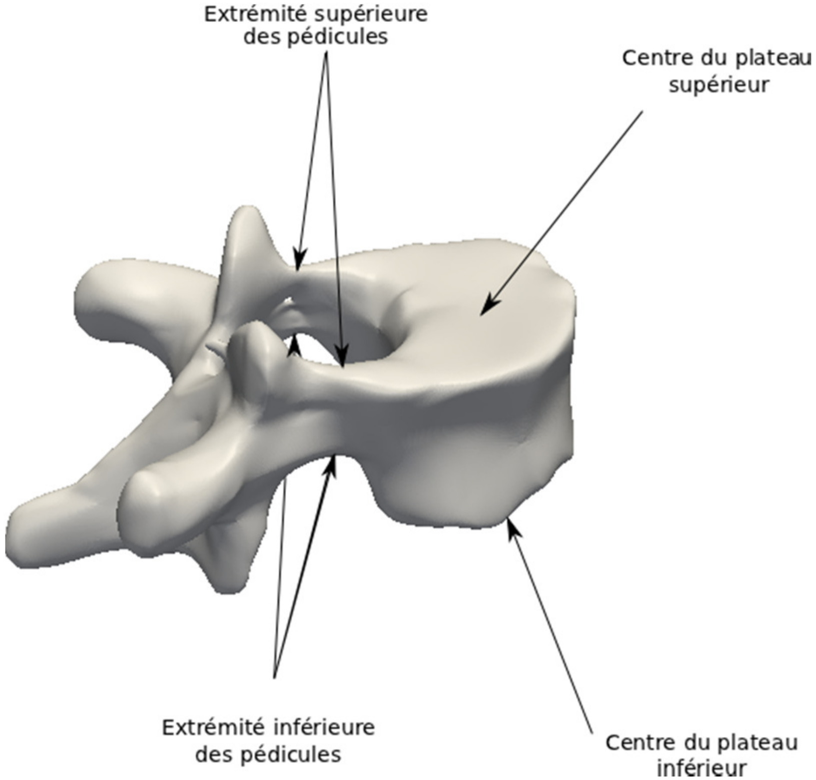
Two Particular Kernels

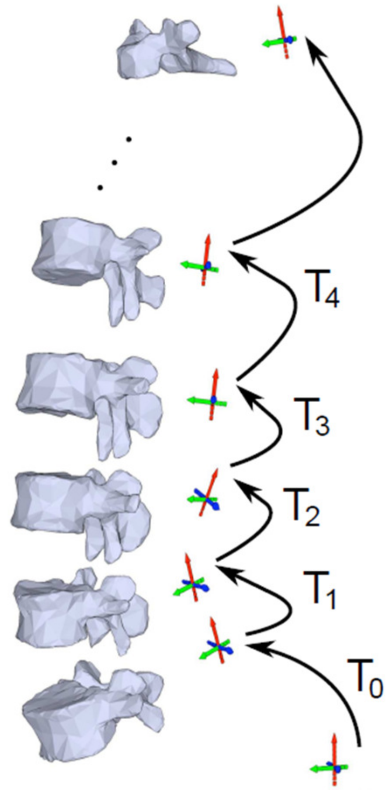
- Hyperplane is defined by a kernel
- A kernel is actually a similarity measure
- Proposed kernel:

RBF : $K(x, y) = e^{-\frac{\|x-y\|^2}{2\sigma^2}}$

Mahalanobis : $K(x, y) = e^{-\frac{(x-y)^T \Sigma^{-1} (x-y)}{\sigma}}$

Two Representations





Representation with landmarks:

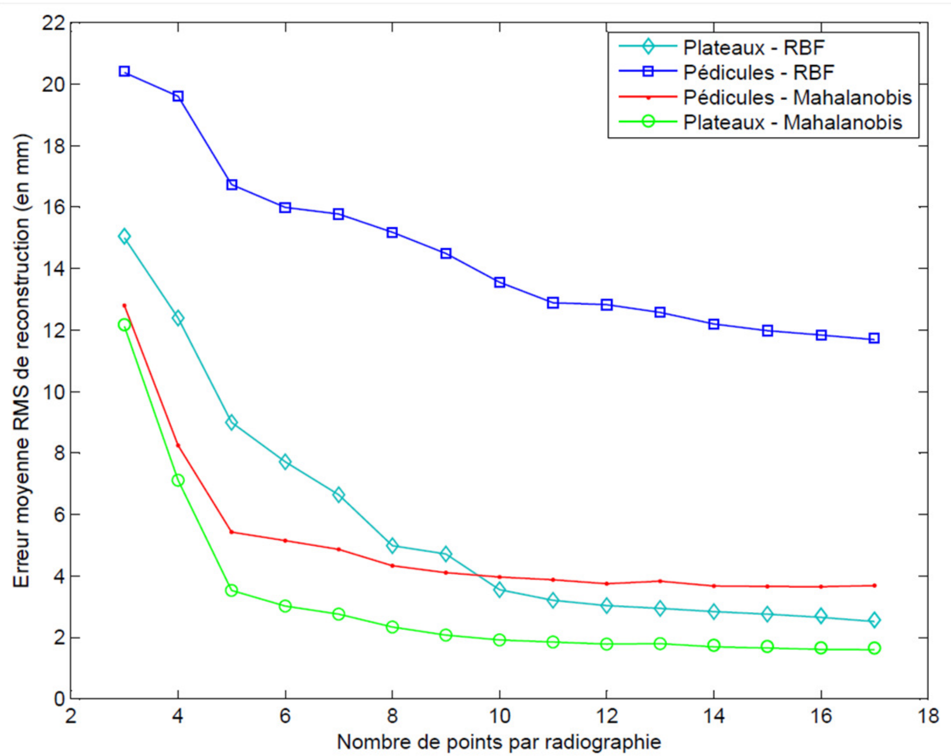
$$X = (p_1^{abs}, p_2^{abs}, \dots, p_k^{abs}, \dots, p_m^{abs})$$

Articulated representation:

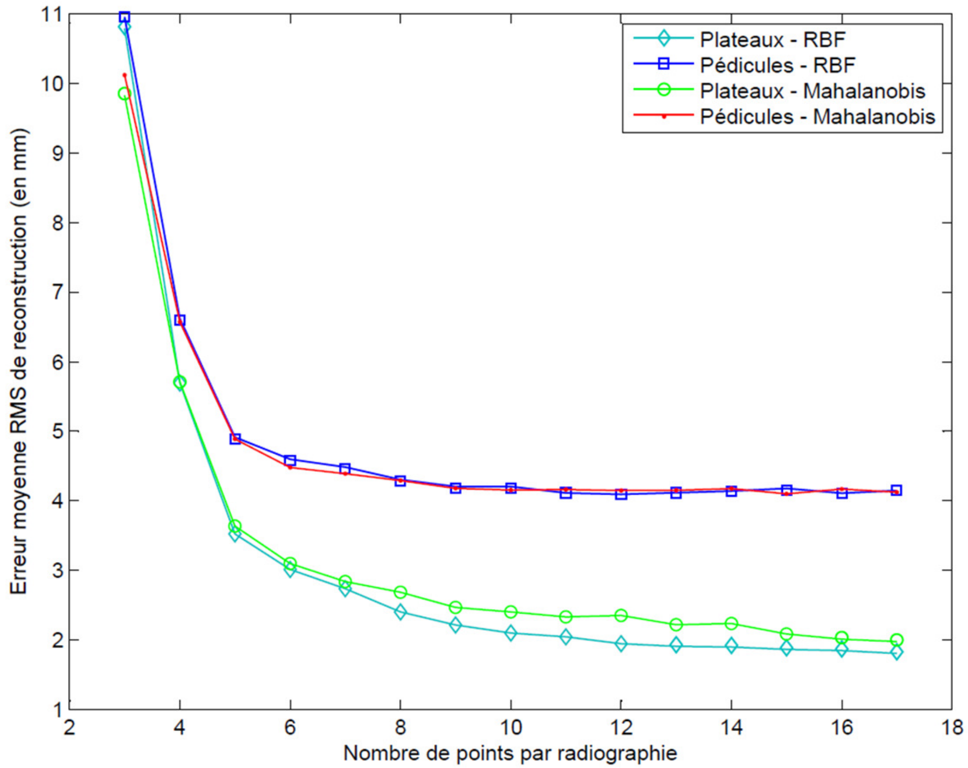
$$X = (T_1, T_2, \dots, T_n, p_{1,1}, p_{1,2}, \dots, p_{n,m})$$

Experiments

Reconstruction Error



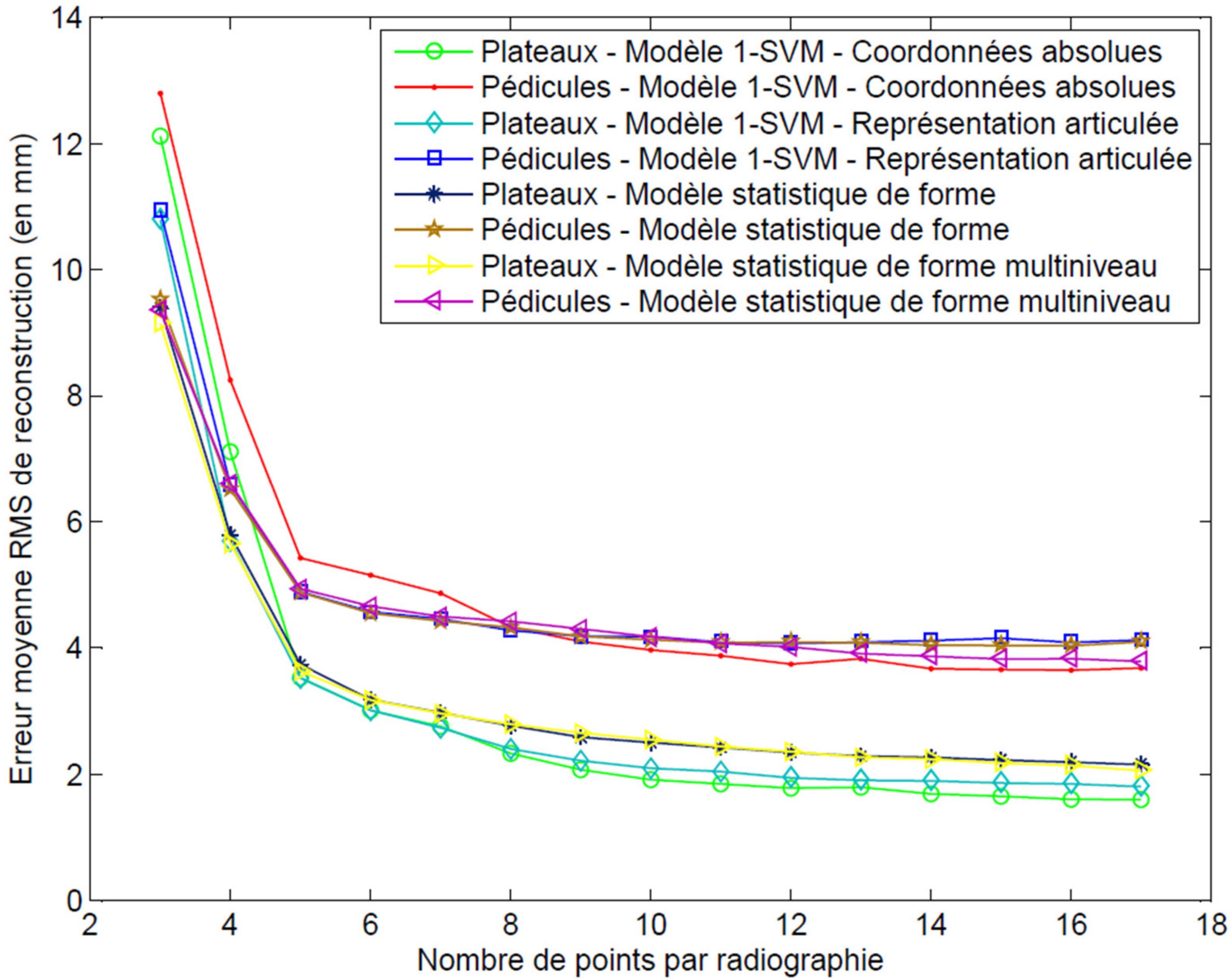
Landmarks



Articulated Representation

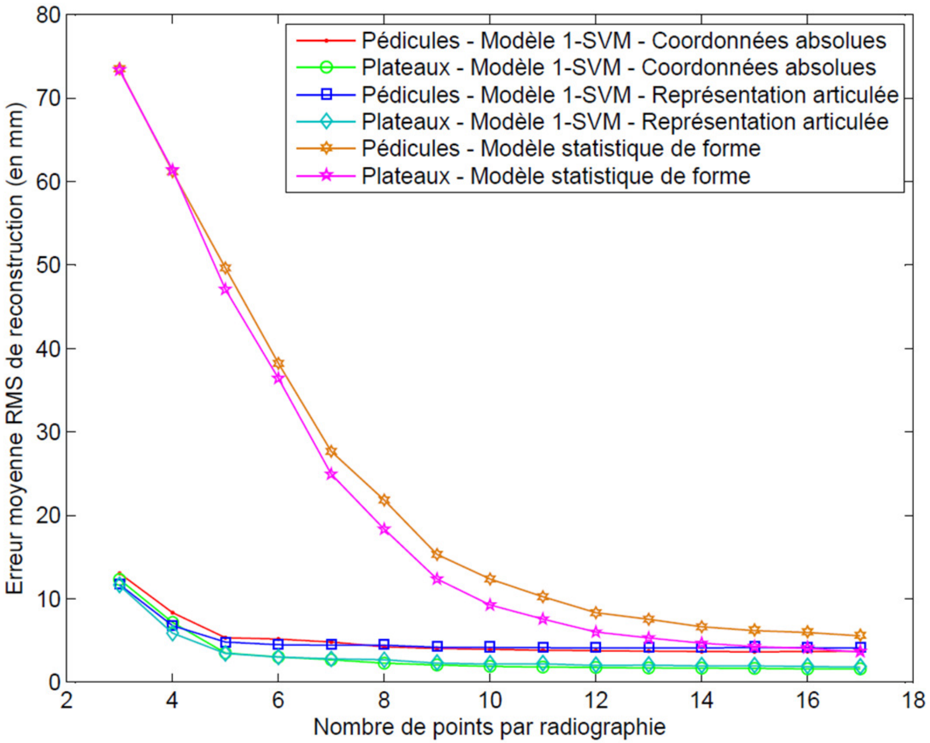
Experiments

Comparison with Statistical Shape Model

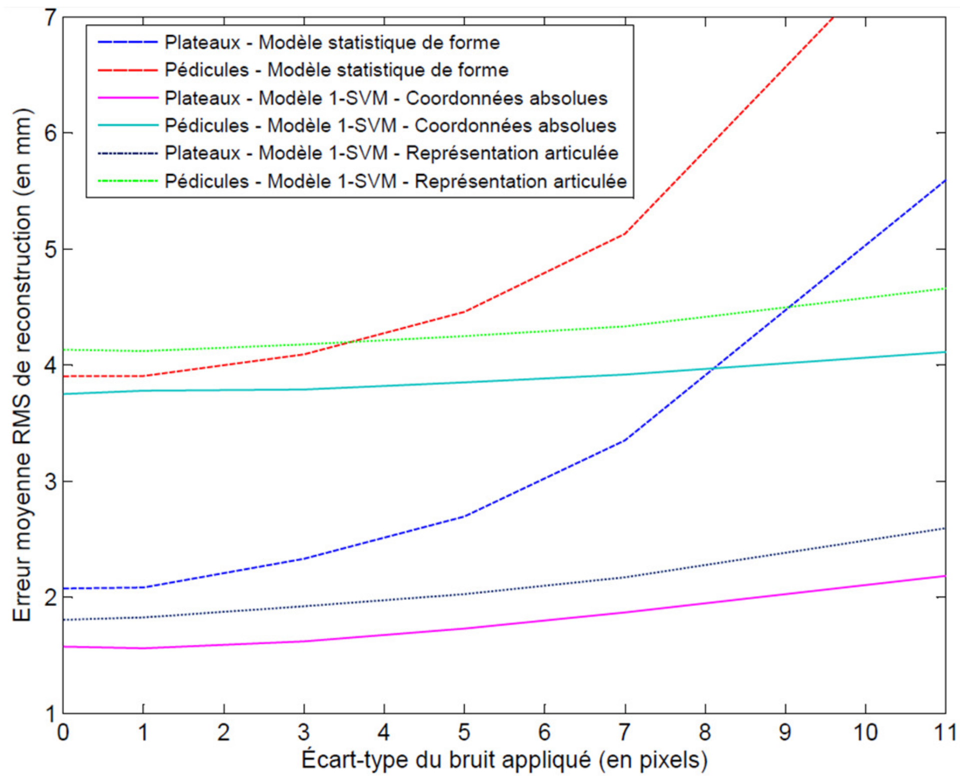


Experiments

$$\min_{w \in \mathbb{R}^n, b \in \mathbb{R}} \frac{1}{2} \|w\|^2 + \frac{1}{\nu m} \sum_{i=1}^{m} \xi_i - b$$



Outliers in the sample



Sensitivity

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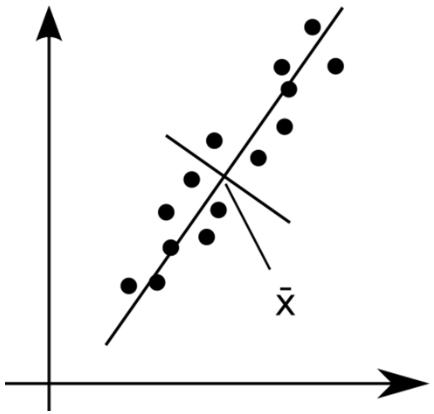
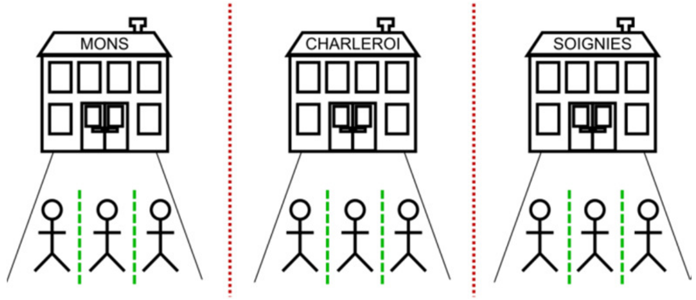
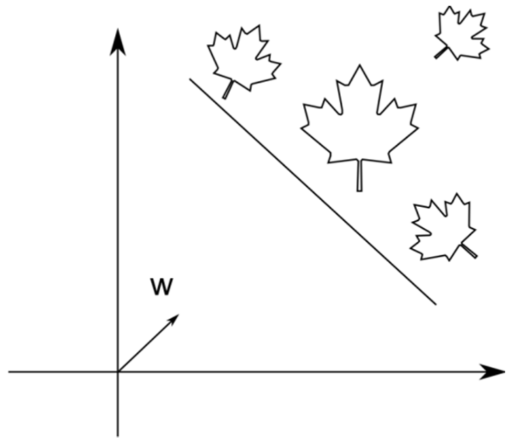
Conclusion



Statistical Shape Model



Multilevel Statistical Shape Model



Machine Learning-based Shape Model

→ Interest of these models to extract the shape of the spine in 2D and 3D

→ These models allow to choose conventional radiography instead of more harmful or more expensive modalities

Conclusion

Vertebral Mobility

Contribution : Automatic analysis of cervical vertebral mobility

→ The statistical shape model guides the segmentation

Scoliosis in 3D

Contribution : Interactive reconstruction based on statistical shape models

Contribution : Robust reconstruction based on OCSVM

→ Reduction of the human intervention

Future Work

Models

- Can be applied to other « objects » (e.g. organs of the human body, etc.)
- Can be used as statistical tools to study a pathology (e.g. evolution of vertebral deformations over time)

Vertebral Mobility

- Extension of the approach to other modalities (e.g. videofluoroscopic system)?
- Other descriptors?

Scoliosis in 3D

- What about EOS system?
- OCSVM: simpler similarities
- Kernel-PCA so that the OCSVM shape model can be used as a statistical tool