BFTA 2011

Belief function theory for image and signal processing

« De omni re scibili...et quibusdam aliis ! »

Olivier Colot

Université de Lille 1

Université Lille1 Sciences et Technologies

cnrs

LAGIS

1

Outline

1. Introduction
2. Applications of BFT to medical imaging
3. Applications of BFT to color imaging
4. Application of BFT to 3D computer generated images
5. Application of BFT to multi-object tracking (not presented)
6. Conclusions

Introduction

- Why BFT in image (and signal) processing ?
- For what ?
- Warning : basics on BFT are required (see previous lectures)

Why BFT ?

☞ **Some words to justify the use of Belief Function Theory in the following applications**

- All the applications are considered in a multisource context
- They need a fusion process (data, features)
- The data are imperfect (uncertain and/or imprecise)
- Possibility of missing data

BFT
applied to MR Images

Topics :

- *Processing (segmentation)*
- *Analysis*

Applications :

- *Brain cancer*
- *Prostat cancer*

5

Medical imaging





Acquisition of image data



+

Segmentation

Filtering

Classification

Registration

Reconstruction



king

6

Medical imaging

Many techniques are nowadays available :

Anatomical imaging:

- US
- CT
- **MRI → some technical basics are following**

Functional imaging:

- PET
- fMRI
- …

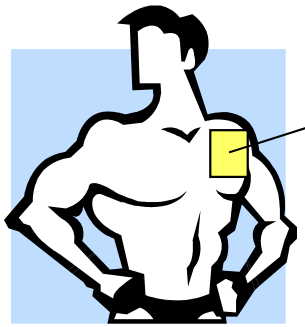
Some basics of MRI

- **Background** :
  - MRI technique exploits the magnetic properties of the atomic nuclei [Bloch-46], [Purcell-46]
  - A patient is submitted to a uniform magnetic field B_0
  - Excitation of the hydrogen nuclei (80% of the body mass) with a radio frequency field of weak intensity *
  - Measure of the energy restored by protons to create the images
  - Multi echo imaging sequences are possible. They use a series of echoes acquired as a train following after a single excitation pulse.

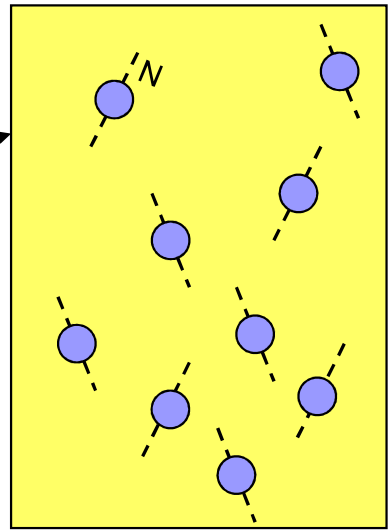


* : The excitation of hydrogen nuclei results in a change in the orientation of their magnetic moments (*i.e.* direction of the respective magnetic fields) away from the main magnetic field of the MRI scanner.

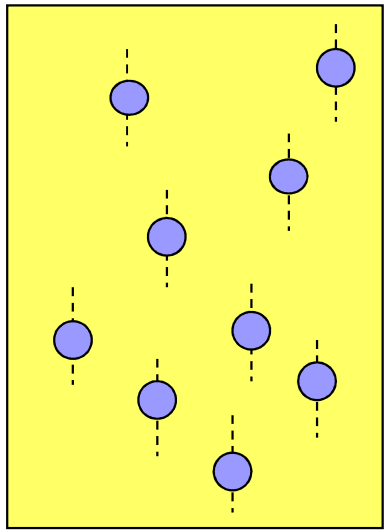
Some basics of MRI

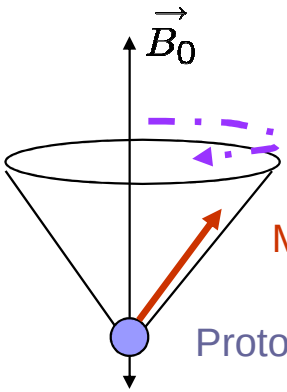


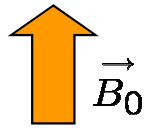
A part of your body



The same part of your body in the machine

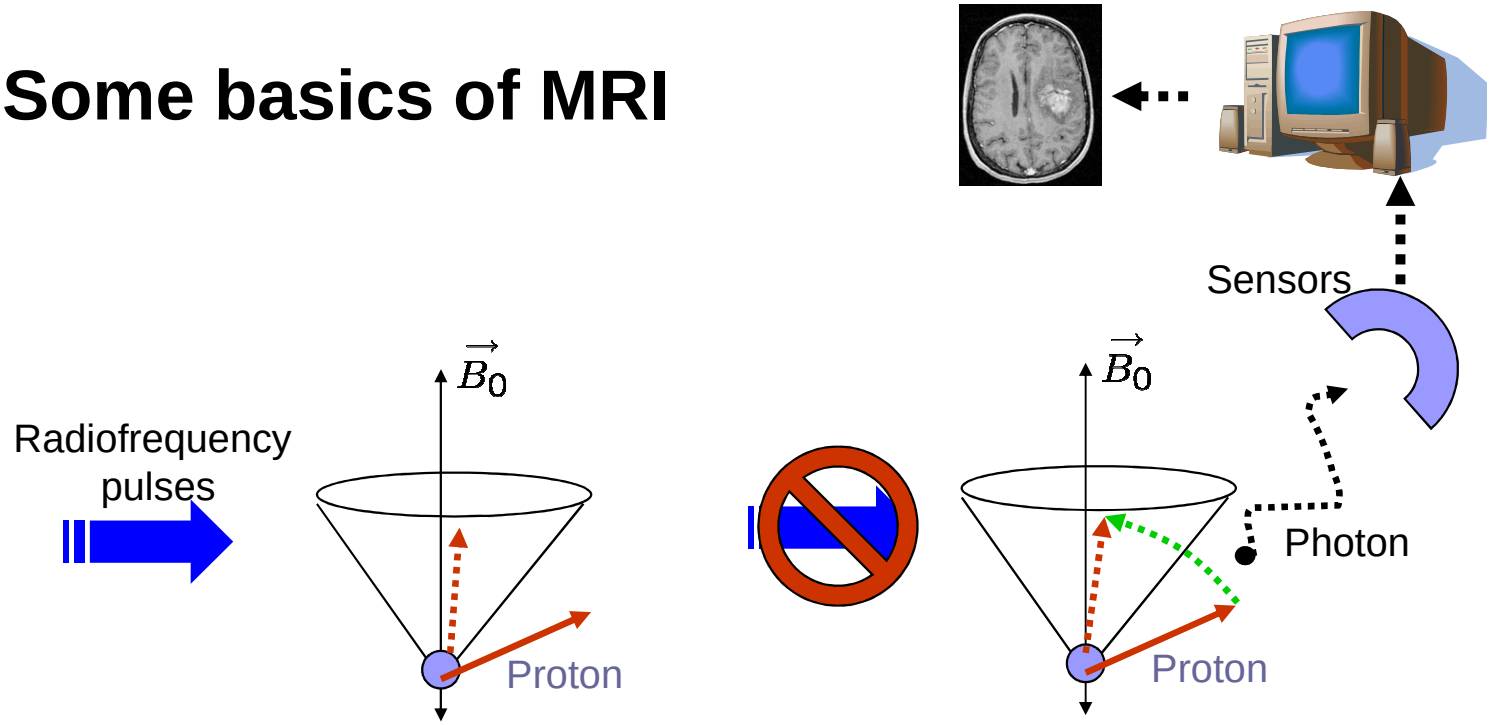






9

Some basics of MRI



The excitation of hydrogen nuclei results in a change in the orientation of their magnetic moments (*i.e.* direction of the respective magnetic fields) away from the main magnetic field of the MRI scanner.

Back to equilibrium involves emission of photons (to capture !)

Why BFT in medical imaging ?

- Multimodal imaging, multi-echoes (MRI)
  $\rightarrow$ multisource context thus fusion process is an option

- Large amount of data (CT and MRI generate stacks of images)

- Diagnosis made by a human expert needs the examination of a lot of images $\rightarrow$ computer aided diagnosis.

- Variance intra and inter examiners (well-known problem inducing uncertainty and imprecision too)

First application : detection of brain tumors

Some references :

A.-S. Capelle, « Segmentation d'images IRM multi-échos tridimensionnelles pour la détection des tumeurs cérébrales par la théorie de l'évidence », Ph.D. Thesis, University of Poitiers, 2003.

A.-S. Capelle, O. Colot and C. Fernandez-Maloigne, "Evidential segmentation scheme of multi-echo MR images for the detection of brain tumors using neighborhood information", *Information Fusion*, Elsevier, **5**(3), 2004, pp.203-216.

A.-S. Capelle, O. Colot and C. Fernandez-Maloigne, "3D Segmentation of MR Brain Images into White Matter, Gray Matter and Cerebro-spinal Fluid by Means of Evidence Theory", *Lecture Notes of Computer Science*, 2780, Springer, 2003, pp. 112-116.

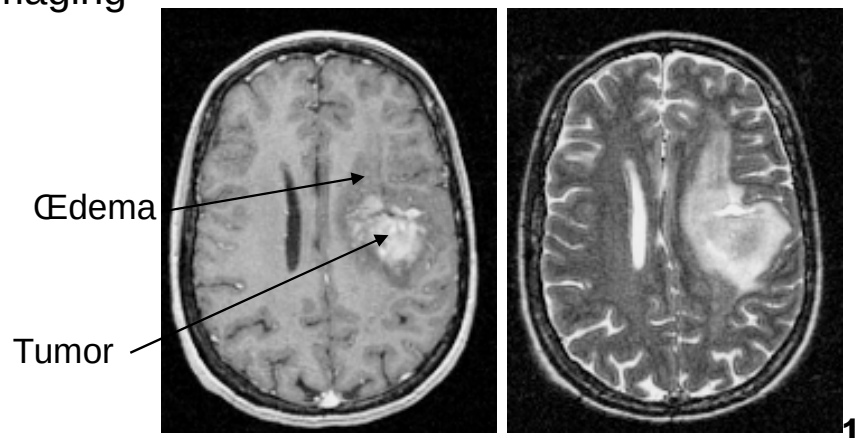
Context

Diagnosis of brain tumors

- Suspicion of tumor
- Validation (or not) by means of imaging
  - CT
  - Scintigraphic imaging (*e.g* PET)
  - Magnetic Resonance Imaging
- Study of the tumors
  - Localization
  - Number
  - Volume

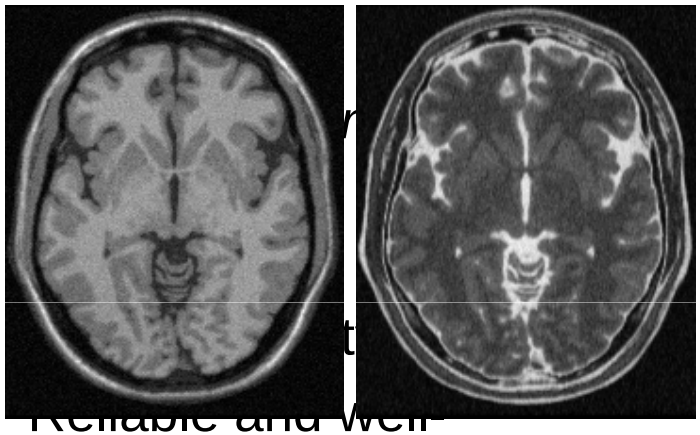
Segmentation of MR images

- Divide the images into regions to obtain the localization of the tumors
- Particularly for not crisp tumors

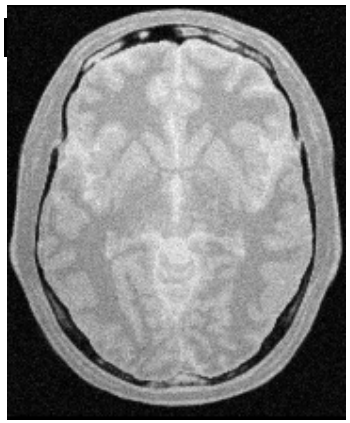


13

MRI : characteristics



T_2



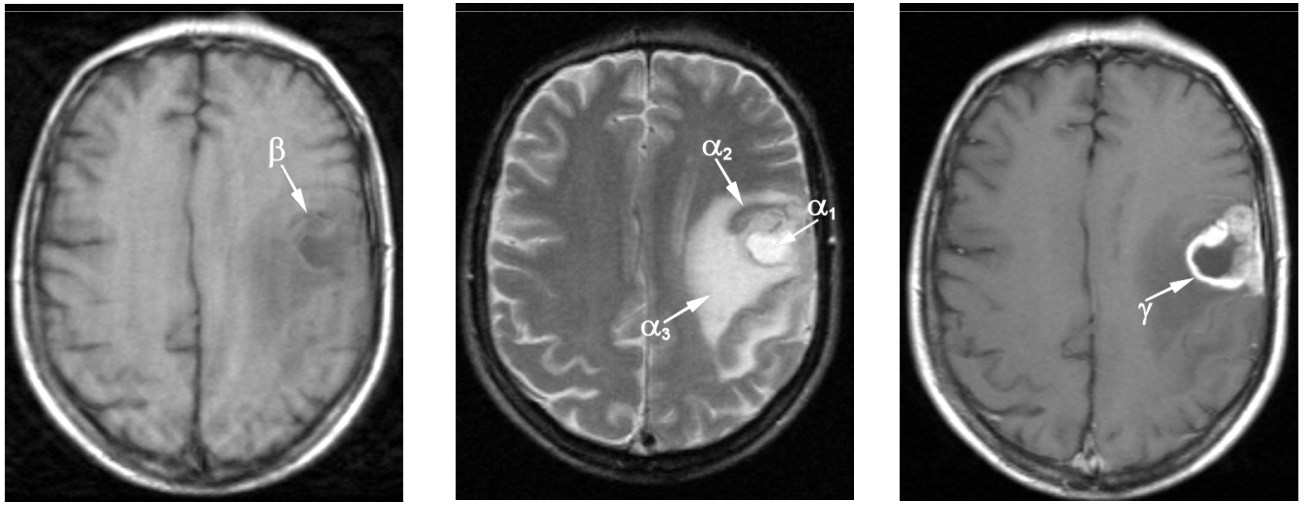
DP (ρ)

- Image contrasts depends on acquisition parameters (T_R, T_E)
- ➔ Possibility to obtain several « views » (observations) of the same organ

MRI : characteristics

- MR images : particularly interesting in the diagnosis framework of brain tumors

Complementary points of view

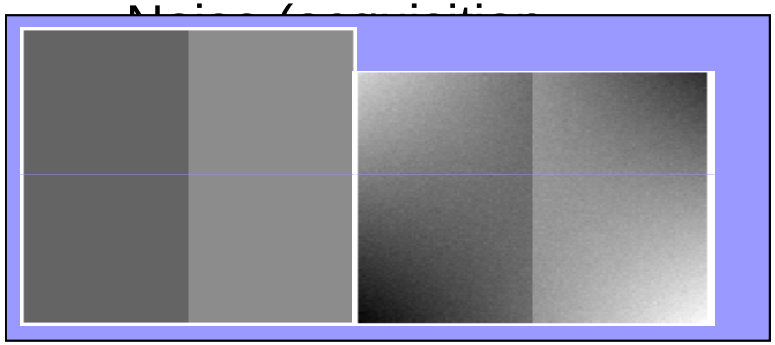


T_1 T_2 T_1Gado

15

MRI : characteristics

Defects



- Defect of the radiofrequency field (non uniform in the space)
- Scanner 1.5T : 20 % up to 30 % [Meyer-95]
- Methods of correction
  - Preprocessings
  - Simultaneously with the segmentation process

Summary

Segmenting tridimensionnal MR images to detect brain tumors

- Tumors with no well defined contours, invasive
- Characteristics of MR imaging
  - great sensibility – multi-echoes
  - imperfections

17

Remarks

« Image » approaches

- recognition/identification of a bi/tridimensionnal signal
  - Thresholding [Kapouleas-90], [Tsai-95] multi-echoes – tumors of white matter
  - Region growing (homogeneous tumors – position of the germs)
  - Snakes

- Not widely used because require (often) the contribution of prior information (location, form, radiometric level…)

Remarks

Pattern recognition approaches

- Define criteria for clustering for allocating voxels to a class
- Methods based on confidence mesures
  - Probability theory (paramétric or not)
    - Gaussian modelling – tumors = *outliers*
  - Fuzzy set theory and possibility theory (partition by FCMs)
  - Belief function theory (BFT)

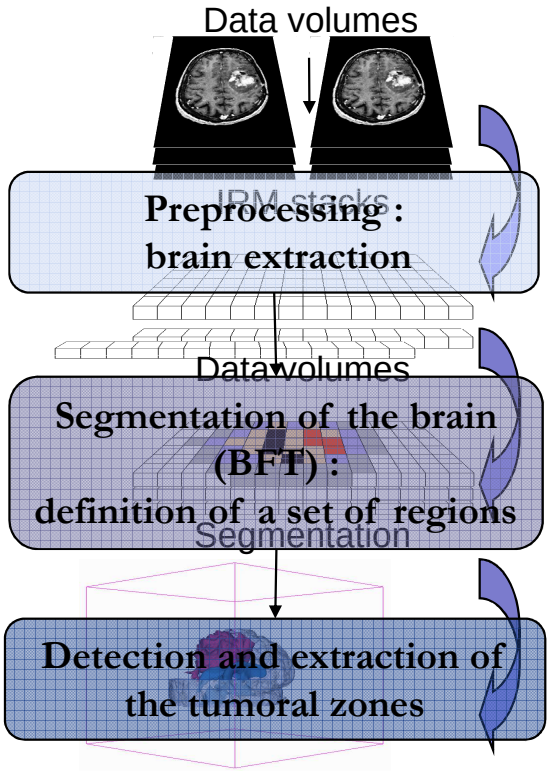
- The most used methods
- But necessary to take into account contextual information

Segmentation process

The essential aspects :

1. Adaptation to the diversity of the images, the radiometry, the tumors → less *a priori* as possible, learning for each case
   - ➔ Pattern recognition
2. Exploiting all the modalities of acquisition at our disposal
   - ➔ Multi-echoes
3. Integrating the imperfection of the data and of the tumors
   - ➔ Belief function theory
   - ➔ Include the spatial dimension in the data processing

Segmentation process



Detection and reconstruction of the tumor

- BFT
  - ➔ Consideration of the imperfect nature of the data
- Multi-echoes
  - ➔ Consideration of the redundancy and the complementarity of the data
  - ➔ a point *s* in the space is modelised by a vector of dimension *p*
- Each point of the volume is assigned to an hypothesis (class) taking into account the spatial neighborhood
  - ➔ segmentation and not only clustering

Preprocessing

Aims :

- To obtain the ROI (brain) in images

Difficulties :

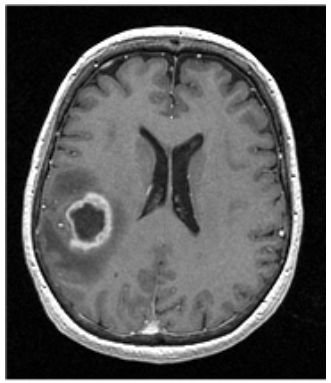
- Tumors have variables characteristics
- Keep these tumors

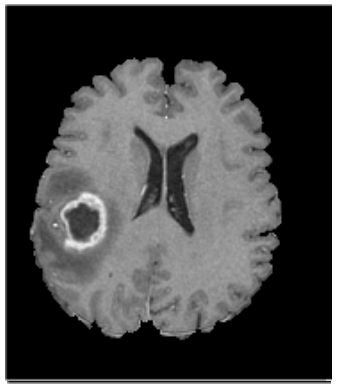
Proposition :

- To adapt existing processing techniques to brain volumes containing tumors

Principe :

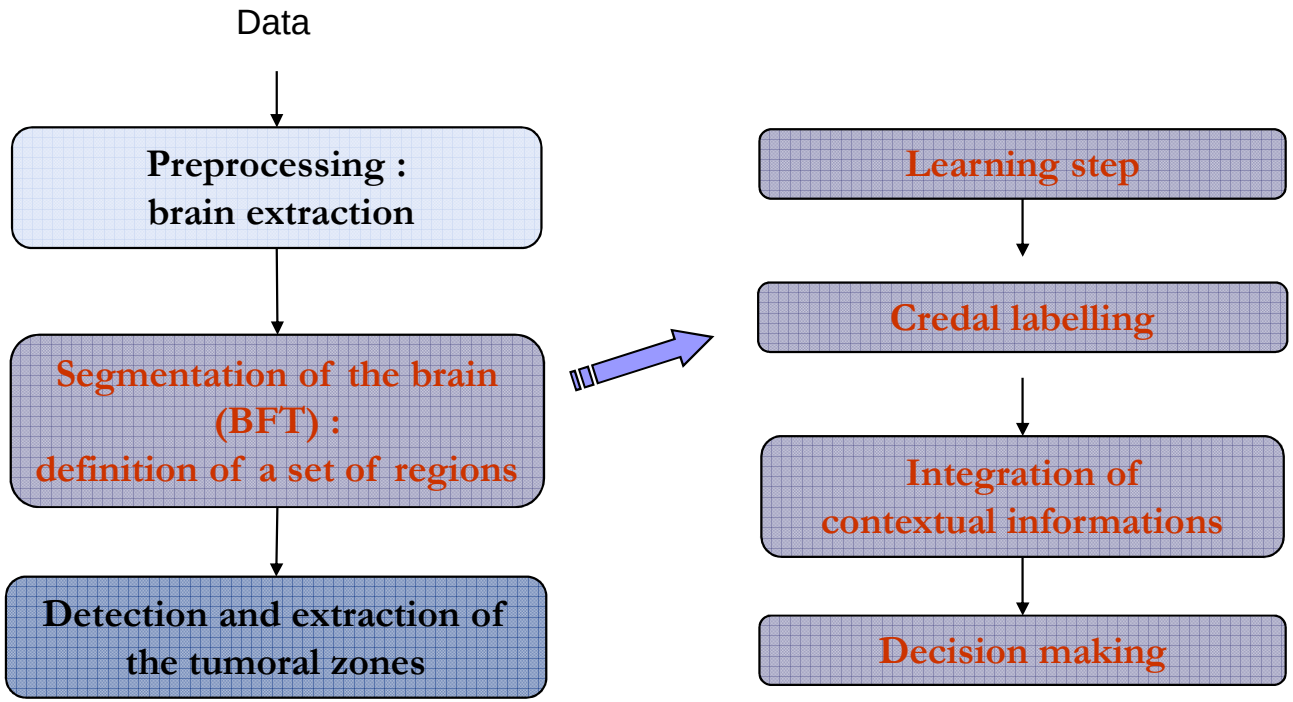
- Thresholdings and mathematical morphology operations





6.1 Result of the initial thresholding

Segmentation process

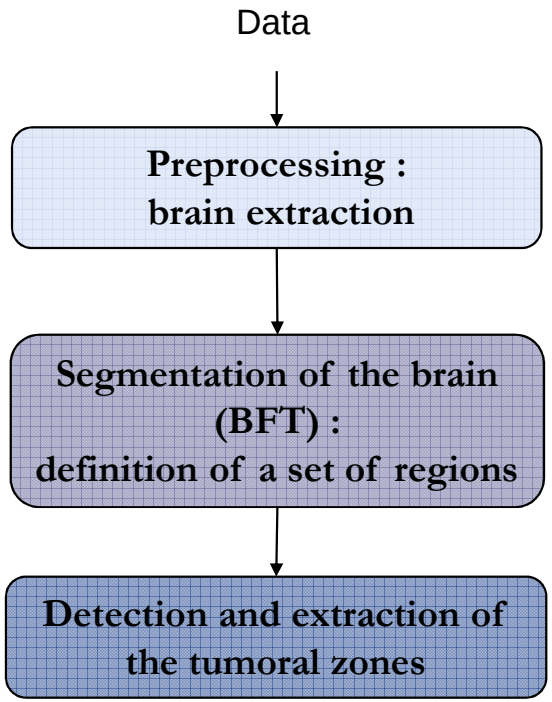


Belief mass modelling

- Use of 3 models
- Distance-based model [Denœux-95]
- Likelihood-based models [Shafer-76] and [Appriou-91]

☞ 3 tested models

Segmentation process



Summary of needs

1. Number of class
2. Likelihood functions
3. Class prototypes
4. Type of distance

Segmentation process

Learning step

Background

- EM algorithm under the following hypotheses :
  1. Number of classes fixed
  2. Gaussian modelling of the classes
- Estimates of means and variances
- Allows to compute the likelihood
- Location of prototypes
- Allows the computation of Mahalanobis distances

In practice

Need to define the learning set

Constraint : to have samples for each class (in particular for class « tumor »), without *a priori* knowledge about the class for each pattern

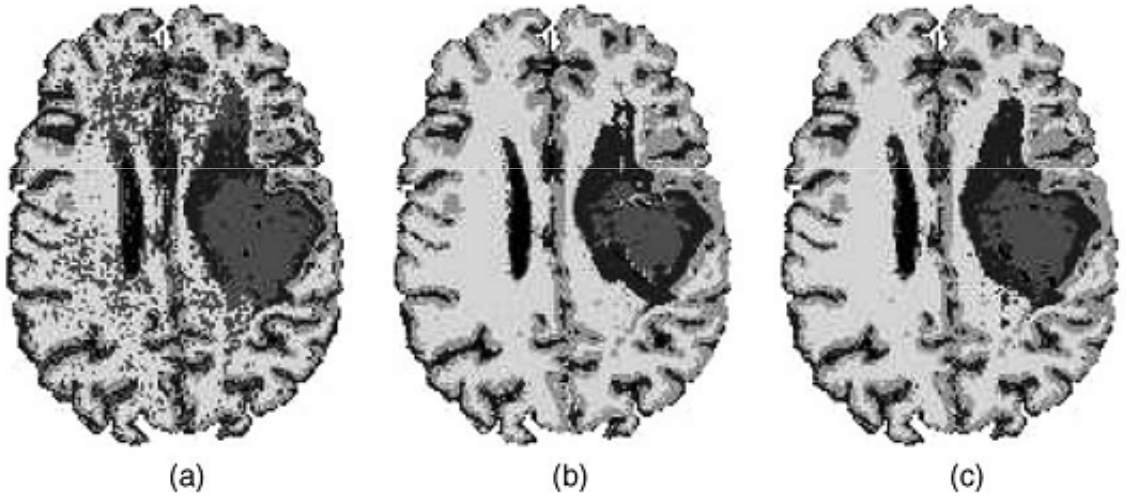
➔ Learning set = set of patterns associated to the volume

➔ Great amount of points

➔ Limits the possibility to improve the learning

Segmentation process

Credal labelling



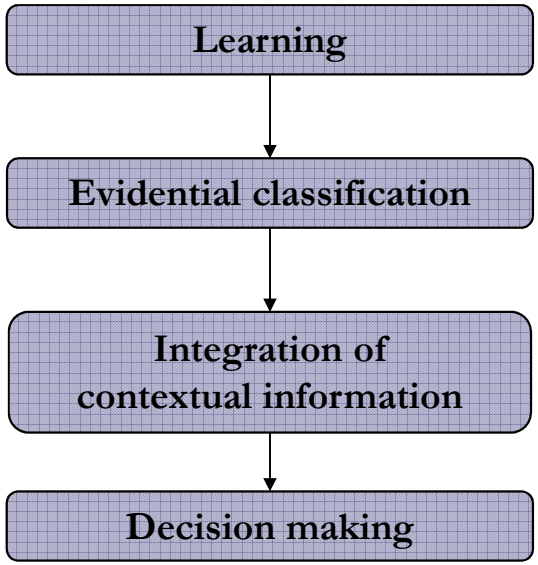
Distance-based model

Likelihood-based model

Likelihood-based model (Shafer)

Segmentation process

Contextual (spatial) information



Aims

- Denoising of the data (evidential filtering)
- Considering the spatial neighborhood (*point* to *region*)

➔ A real segmentation process

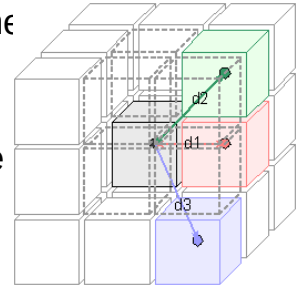
Principle

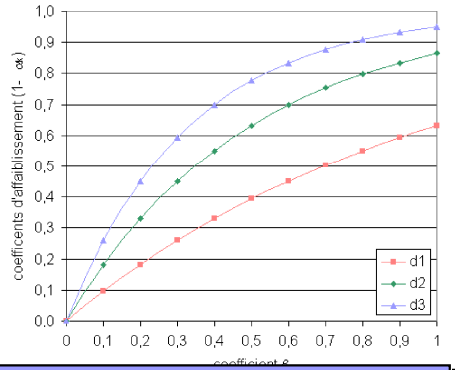
- Consider every neighbor as an information source able to improve the knowledge
- Combine these informations in the framework of BFT

Segmentation process

Contextual (spatial) information

1. One voxel => a mass (issued from the classification process)
2. Consider each voxel relatively to its neighborhood taking into account the distance between the point and each considered neighbor





   - ➔ Discounting of the masses associated to the neighbors

$$\alpha_q = \phi(d^2(q))$$
$$\text{with } d_q = d(p,q)$$

$$\phi(d^2(q)) = \exp(-\beta d_q^2)$$

3. Fuse these masses with Dempster's rule of combination

$$m' = m \bigoplus_{q \in \{1,\ldots,Q\}} m_q^{\alpha_q}$$

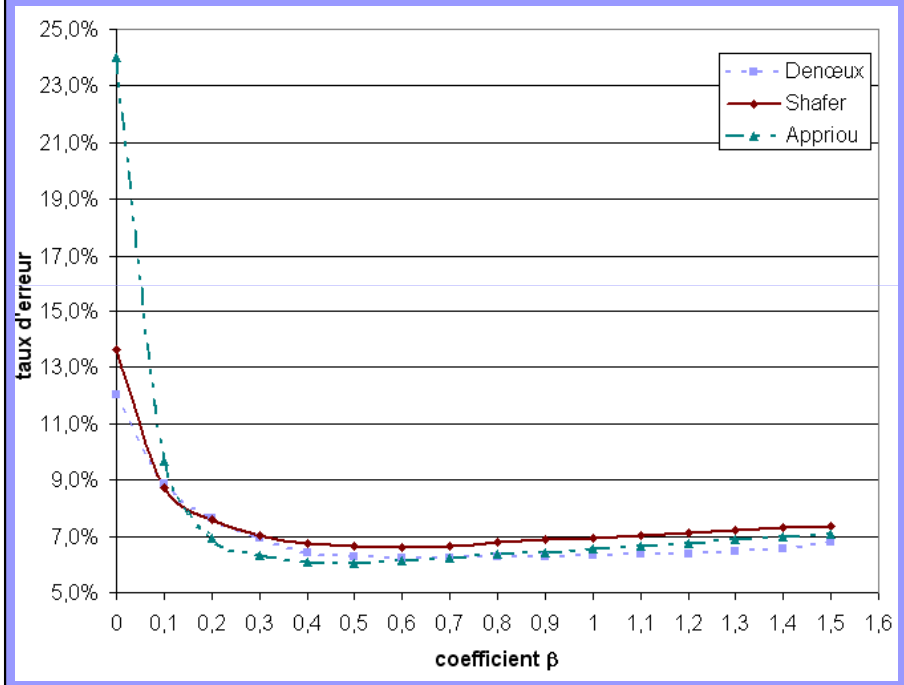
Brainweb database

- Free access database
- Synthetic volumes (computer generated images) of the human brain
- Different sequences {T_1, T_2, DP}
- Different noise levels (3%, 5%, 7%, 9%)
- Differents levels of the radiofrequency field drift (0%, 20%, 40%)
- **Known ground truth**

Segmentation process

contextual information

Error rate vs. discounting



Niveau de bruit : 7%, niveau de dérive : 20%

- β low:
  - Important error rates
  - Too large Influence of the neighbors
  - Neighbors = sources of noise
- Based on the whole set of volumes

$$0{,}5 \leq \beta_{opt} \leq 1{,}5$$

- $\beta > \beta_{opt}$
  - New increase of error rates
  - Suboptimal influence of the neighbors

$$\xi_{|\beta \to \infty} = \xi_{|\alpha_i = 1} = \xi_{classification}$$

30

Segmentation process

Contextual information

1. One voxel => a mass (issued from the classification process)
2. Consider each voxel relatively to its neighborhood taking into account the distance between the point and each considered neighbor
   - ➔ Discounting of the masses associated to the neighbors

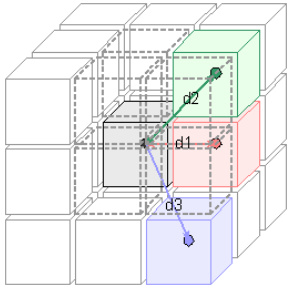
$$\alpha_q = \phi(d^2(q))$$

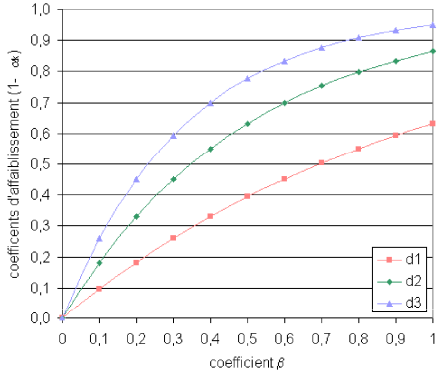
with $d_q = d(p,q)$

$$\phi(d^2(q)) = \exp(-\beta d_q^2)$$

3. Fuse these masses with Dempster's rule of combination

$$m' = m \bigoplus_{q \in \{1,ldots,Q\}} m_q^{\alpha_q}$$





Optimal value for β ?

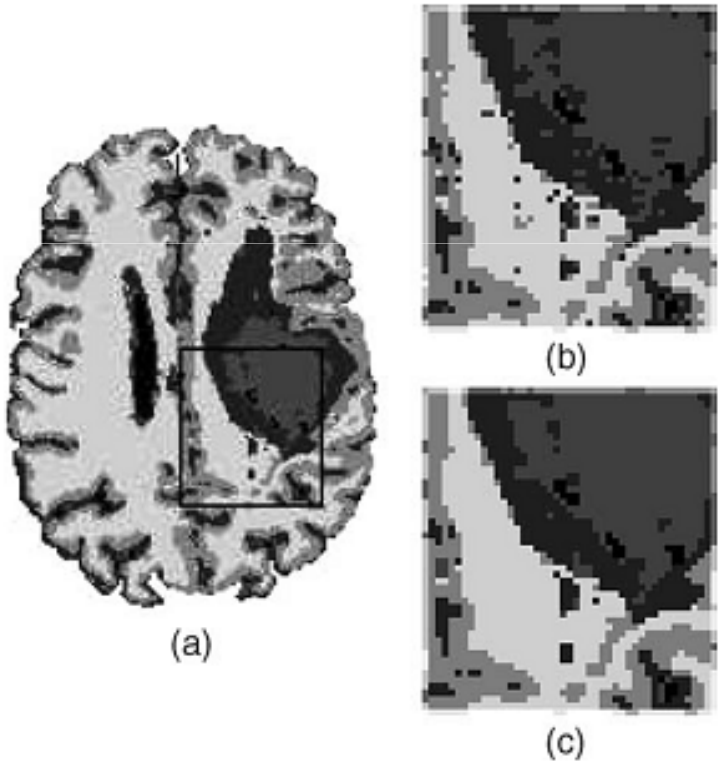
- ➔ Heuristically determinated by the use of *Brainweb* database

$$\beta_{opt} = \arg \min_{\beta \in [0,+\infty[} \{\xi(\beta)\}$$

$$\boxed{\beta_{opt} = 0{,}6}$$

Segmentation process

Contextual information



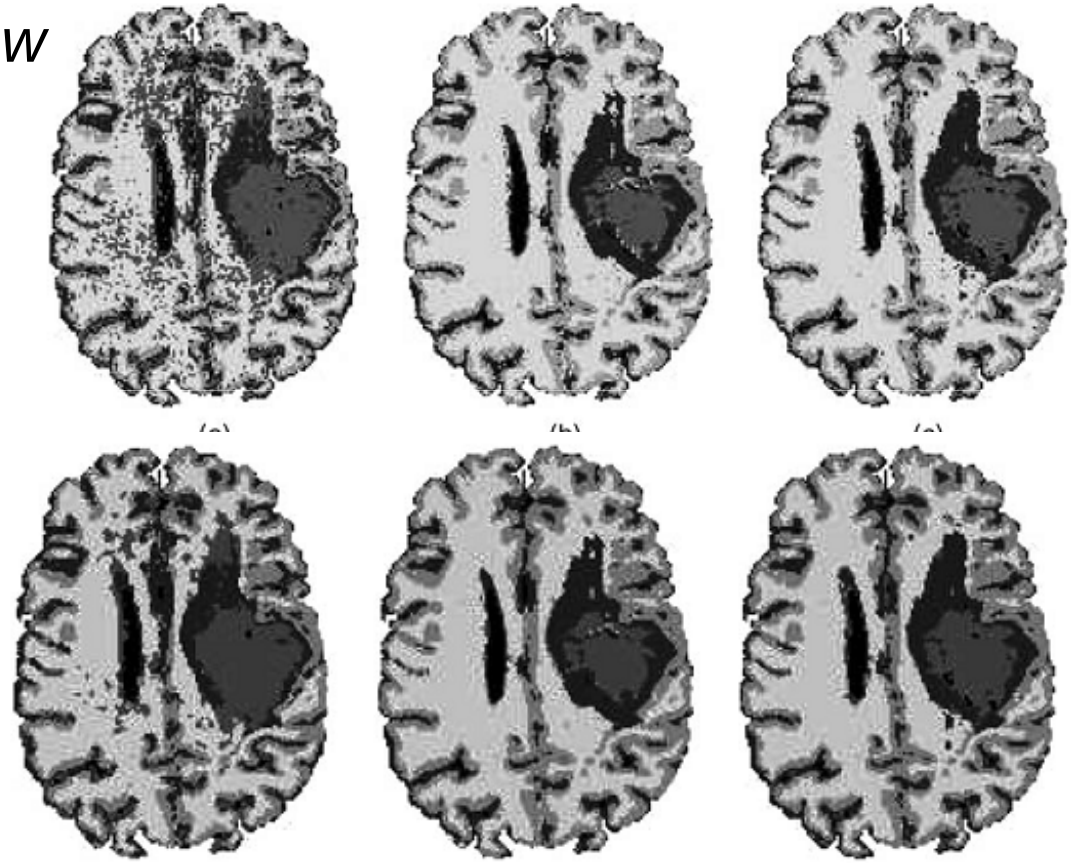
Without contextual information

With contextual information

☞ filtering

Segmentation process

Overview



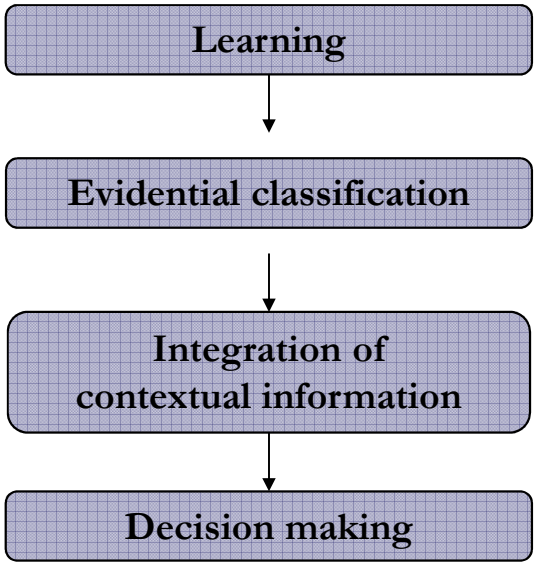
(a) **Distance-based model**

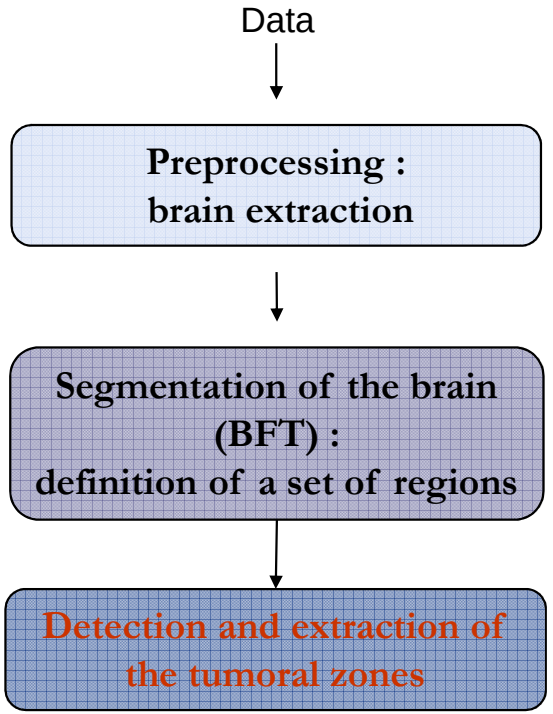
(b) **Likelihood-based model**

(c) **Likelihood-based model (Shafer)**

Segmentation process

Decision making





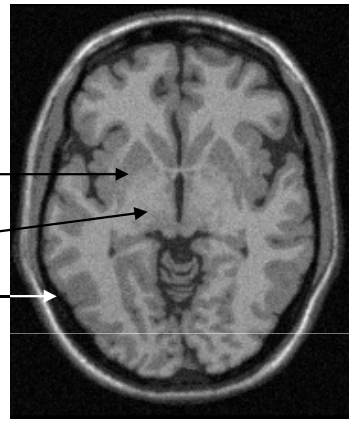
- Maximization of the pignistic probability
- Maximization of the plausibility

Validation on synthetic data (*Brainweb*)

1st level : evidential labelling

(without contextual information)

- 3 classes (WM – GM – CF)
- Error rate
- Comparison with C-means, FCM and EM



T_1

- Best performances when close to real conditions (n ≥ 5%, rf ≥ 20%)

Validation on synthetic data (*Brainweb*)

2nd level : segmentation

(with contextual information)

- Comparison clustering – segmentation
  - Decrease of the error rates
  - Smoothing of the regions while preserving the thin structures
- Comparison with probabilistic methods
  - EM + Markov random fields
  - [Leemput-99] (EM + *prior* informations) + Markov random fields + drift correction

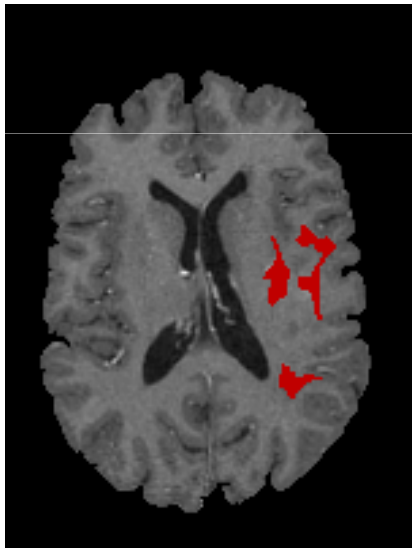
Segmentation of real data stacks

- Data provided by CHRU of Poitiers {T_1 – T_1Gado} et {T_1Gado – T_2}
- No need of registration between the stacks
- Number of classes fixed (depending of the studied case). In general
  ={WM, GM, CF, tumor, œdema}

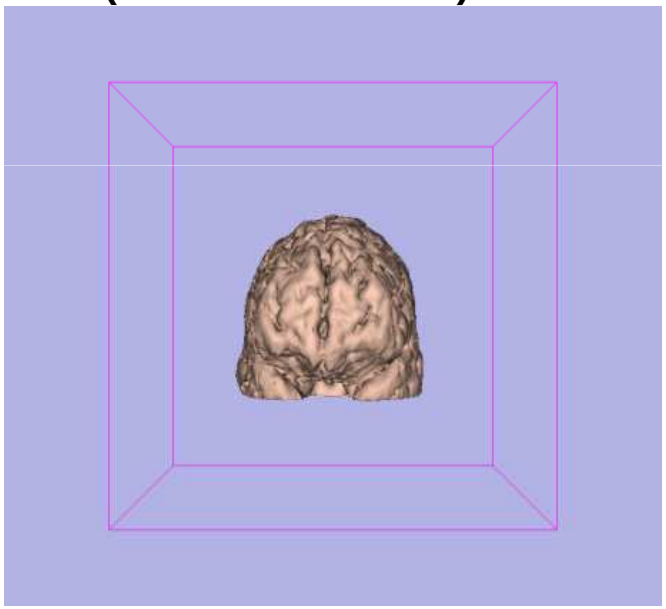
- Validation : comparison with a hand-made segmentation (expert)
  - ➔ **Expert dependent !**
- Rates :
  1. Good detection
  2. No détection
  3. False alarm

Segmentation of real data stacks

Images of the stacks



Segmentation results (3D reconstruction)



Spatial combination and conflict

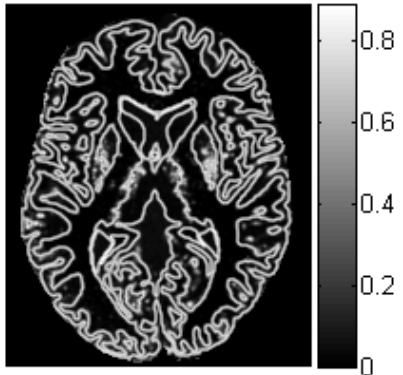
Introduction of contextual information : based on the fusion of neighborhood masses

- ➔ Generate conflict
- ➔ Give information about the amount of discordance between the sources (neighbors)
- ➔ 2 types of behaviour :

1. Homogenous regions : *a priori* sources agree → low amount of conflict
2. Borders : discordance between different neighbors → conflict



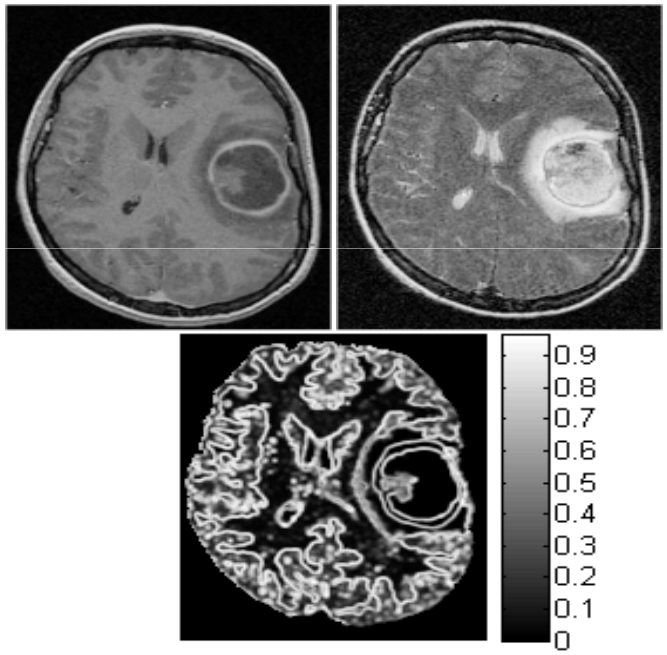
Ground truth



Conflict

39

Spatial combination and conflict



- Conflict : gives information about the borders of the regions

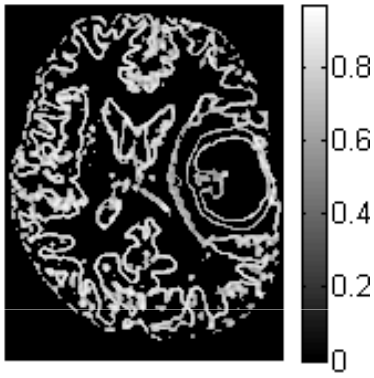
But :

non trivial information

- borders $\Longrightarrow$ conflict
- conflict $\not\Longrightarrow$ border

Conflict : a border indicator

- **Idea** : use the conflict information to complete the segmentation process
- $$\mathbb{I}(x) = \begin{cases} 0 & \text{si } c(x) < \lambda_c \\ c(x) & \text{si } c(x) \geq \lambda_c \end{cases}$$
- Image of the possible localization of the borders

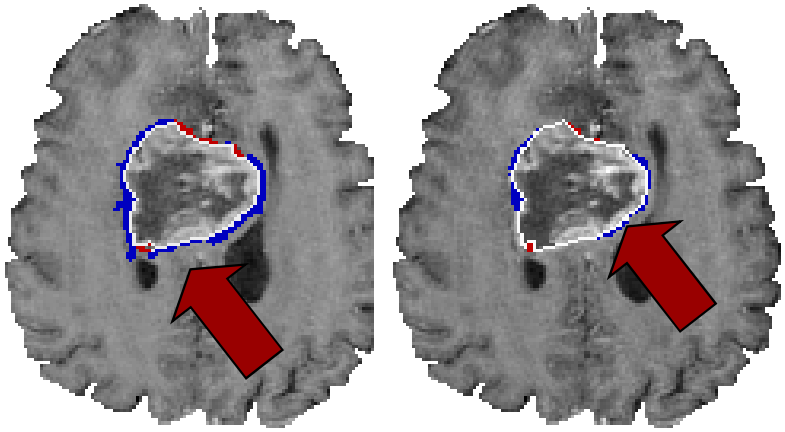




Cooperation « contour-region »

- Segmentation process provides :
  - Regions
  - « Contour » information
- ➔ Towards a cooperation « region-contour » to improve the results

- Experiment : use the borders of the regions to initialize a snake guided by the conflict



42

Remark

Another approach with BF

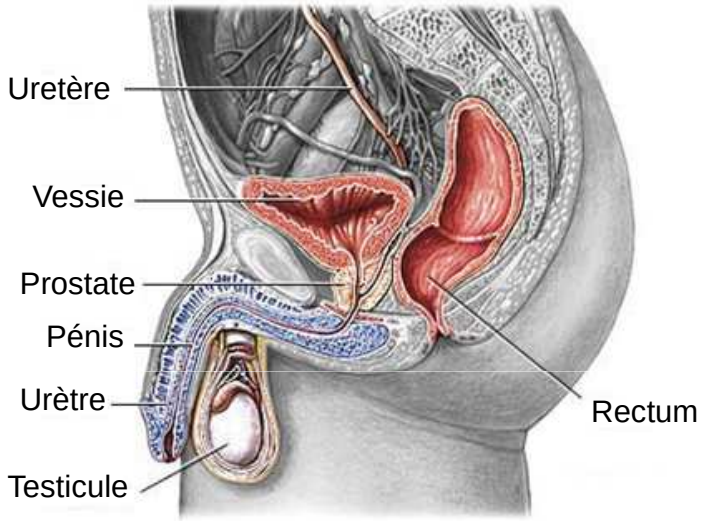
- ECM (T. Denoeux and M. Masson, *Pattern Recognition*, 2008)

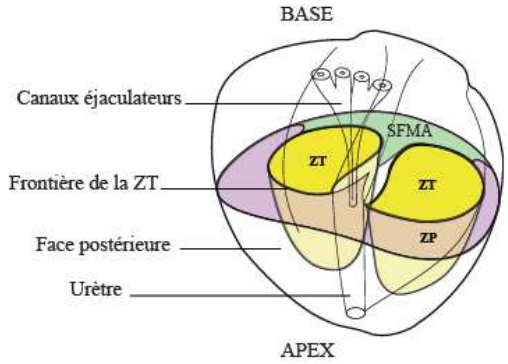
Second application : detection of prostat tumors

Reference

N. Makni, « Méthodes d'identification, d'aide au diagnostic et de planification utilisant de l'imagerie multimodalité pour les thérapies focales du cancer de la prostate », *Ph.D. Thesis*, University Lille 1, 2010,

Prostat cancer





- First cancer of men older than 50 years old*
- 80 % of tumors are located in peripheral zone
- Cancer with slow evolution

45

*: in industrial countries

Unsupervised algorithm

Initial conditions:

$\mathcal{X} = \{X_1, \ldots, X_n\}$ $\quad \Omega_0 = \{\omega_1, \ldots, \omega_n\}$ $\quad t = 0$ $\quad \mathcal{P}_0$

$X_i \in \mathcal{X}$; $\omega_i \in \Omega_0$; $|\Omega_0| = n$

Repeat

  for all pattern vector X_i of $\mathcal{X}$ **do**

    Compute m_i using distance-based model

    Compute the pignistic function $BetP_i$ from m_i

    Take a decision using $\mathcal{R}_{BetP}$ on Ω_t

  end for

  Updates:

    $t \leftarrow t + 1$:

    $\mathcal{P}_t \leftarrow \mathcal{P}_{t+1}$

    $\Omega_t \leftarrow \Omega_{t+1}$ with $|\Omega_{t+1}| \leq |\Omega_t|$

until partition $\mathcal{P}_t$ is stable

Pignistic decision rule

No changes in the decision step

Unsupervised algorithm

For each iteration $\rightarrow$ 2 steps

Step #1

- Estimate the credal partition P

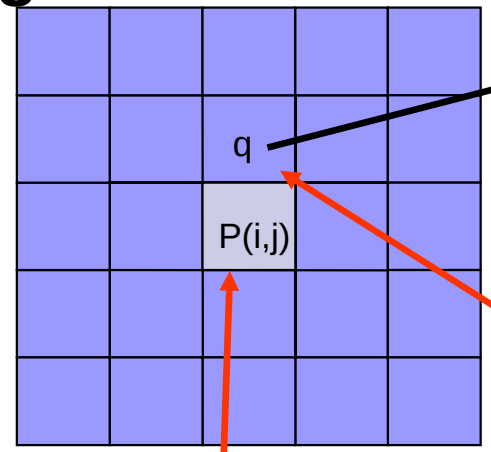
Step #2

- Decision making considering the present partition P with the pignistic decision rule.
- At the end of the step, destroy the empty clusters.
- Updating the membership to clusters which make the new learning set for the next iteration.

What does the process ?

From the initial partition with a great number of cluster, the algorithm estimates iteratively a new partition of the color space. The number of clusters decreases until it reaches a stable partition.

Taking into account the spatial neighborhood



Each neighbors *q* of a pixel *P(i,j)* is considered as an information source S_q

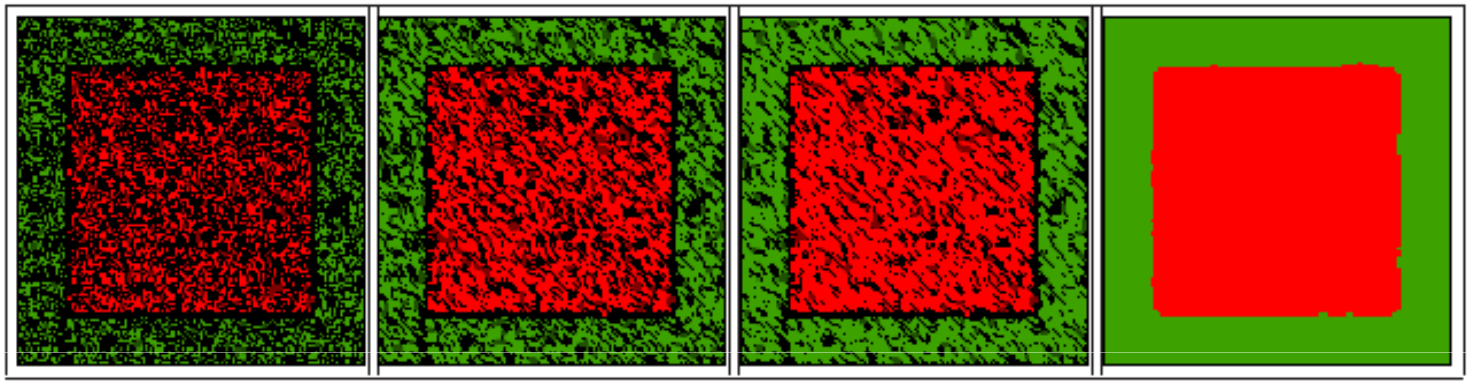
$$m_{\alpha_q S_q}(H_n) = \alpha_q m_{S_q}(H_n)$$

$$m_{\oplus} = m \oplus m_{\alpha S_1} \oplus m_{\alpha S_2} \oplus \ldots m_{\alpha S_q} \ldots \oplus m_{\alpha S_Q}$$

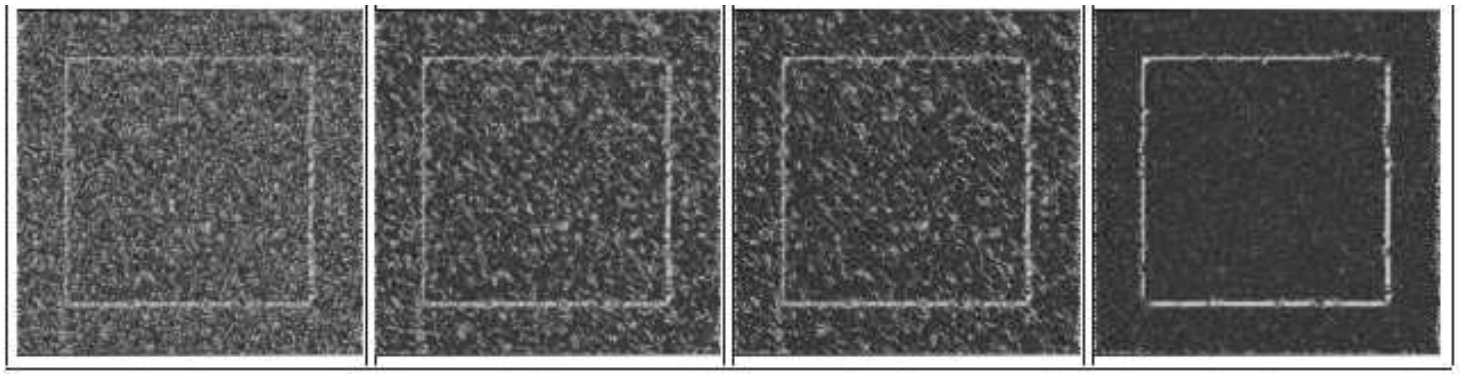
$$\alpha_q = \exp(-(d^{S_q})^2)$$

Discounting the masses according to the distance to the central pixel

Results

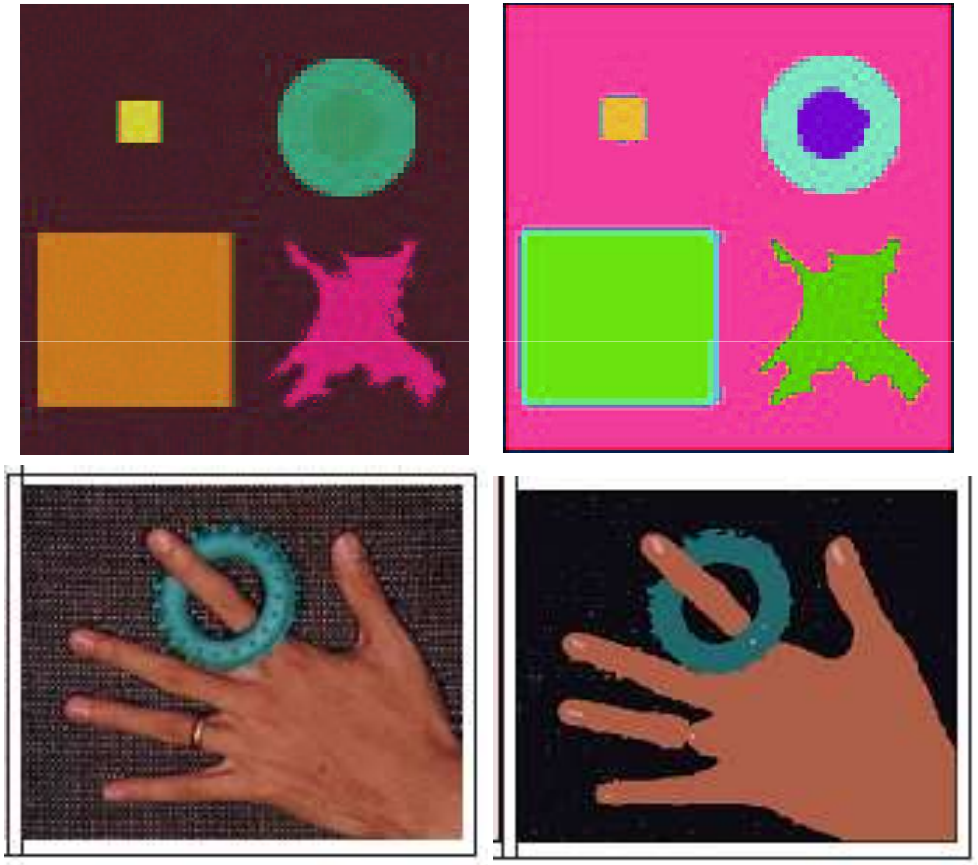


(a) Labeled pixels at the initial iteration step. (b) Labeled pixels at the first iteration step. (c) Labeled pixels at the second iteration step. (d) Labeled pixels at the final iteration step.



(a) Doubt degree at the initial iteration step. (b) Doubt degree at the first iteration step. (c) Doubt degree at the second iteration step. (d) Doubt degree at the final iteration step.

Results



BFT
applied to color image quantization

Reference

A.-S. Capelle, O. Colot and C. Fernandez-Maloigne, "TBM for color image processing: a quantization algorithm", *Proc. of the 9th International Conference on Information Fusion - Fusion 2006*, Florence (Italie), 2006, pp. 1824-1830.

Color image quantization: why?

- **Color images**
  - Size, format, color space,…
  - Numerous colors

Is it necessary to preserve all the colors from a perceptual point of view ?

→ Human eye and noticeable color differences

- **Aim:**
  - Reduce the number of colors of an image
  - ➔Find the **most important colors** in a color image while **preserving** the perceptual quality of an image
- **Application**
  - Image compression

Original image of a beautiful girl

(148279 colors)



Image of the beautiful girl with 256 colors

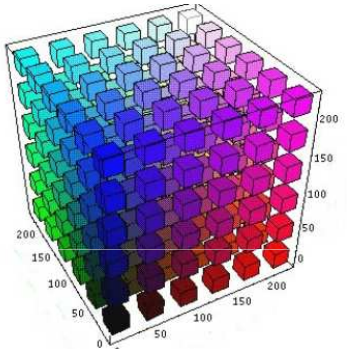


Color image quantization: how?

- **Objective:**
  - Reduce the number of colors of an image

  ➔Find the **most important colors** in a color image while **preserving** the perceptual quality of an image
- **The main approaches:**
  1. Splitting approaches

Splitting algorithms



- The simplest splitting algorithm: the regular quantization
  ➔Divide the RGB cube in regular sub-cubes (bins)
- More elaborated methods: estimate the best axis to divide the RGB cube
  ➔Median-Cut, Octree…

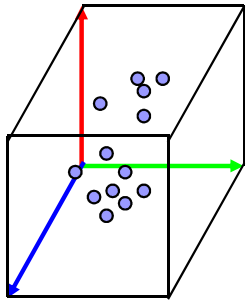
91

Color image quantization: how?

- **Aim:**
  - Reduce the number of colors of an image

  ➔Find the **most important colors** in a color image while **preserving** the perceptual quality of an image
- **The main approaches:**
  1. Splitting approaches
  2. Clustering-based approaches

Clustering-based algorithms



RGB cube = space of characteristics

1. Find the best partition of the color space
   - ➔ C-Means algorithms
   - ➔ Fuzzy-C-Means algorithms
   - ➔ Genetic algorithms
2. Reduced color palette= { representants of each cluster}

92

Color image quantization: how?

- **Another way?**
  - A clustering approach based on the TBM use

The unsupervised algorithm

- The same as for color image segmentation but with some differences (explained hereafter)

The unsupervised algorithm (Credal-Q)

Initial conditions:
$\mathcal{X} = \{X_1, \ldots, X_n\}$ Ω_0
$X_i \in \mathcal{X}$; $\omega_i \in \Omega_0$; $|\Omega_0| = r$
Repeat
  for all pattern vector X
    Compute m_i using d
    Compute the pignisti
    Take a decision using
  end for
  Updates:
    $t \leftarrow t + 1$:
    $\mathcal{P}_t \leftarrow \mathcal{P}_{t+1}$
    $\Omega_t \leftarrow \Omega_{t+1}$ with $|\Omega_{t+1}| \leq |\Omega_t|$
until partition $\mathcal{P}_t$ is stable

Problem:
The final number of clusters is *a priori* unkwown

Our proposition:
Add a new criterion to converge toward a defined number P_d of clusters
➔ Evidential quantization algorithm

No change during decision step

95

Evidential quantization algorithm

- Aim: we want to obtain P clusters
- 4 possible cases at the end of the decision step:
  1. The number of clusters > P ➔ continue
  2. The number of clusters = P ➔ end
  3. The number of clusters < P
  4. The partition is stable but the number of clusters > P

No problem

Problem !!

- Case 3 : proposition
  - Backward step: number of clusters < P
    ($|\Omega_{t-1}| = |\Omega|$ = the previous number of clusters)
  - Find the best P clusters among the $|\Omega|$ clusters: the **R_* rule**

The R_* decision rule

- **Basic idea**: select the *P* most relevant clusters by using the pignistic function:
  - Mean pignistic value associated with a cluster ω_j

$$\overline{BetP(\omega_j)} = \frac{1}{n}\sum_{i=1}^{n} BetP_{X_i}(\omega_j), \quad X_i \in \mathcal{X}$$

  - Mean pignistic vector

$$\overline{BetP} = \left[\overline{BetP(\omega_1)}, \ldots, \overline{BetP(\omega_{|\Omega|})}\right]$$

The R_* decision rule

- Order the mean pignistic values

$$\overline{BetP(\omega_{q_1})} \geq \cdots \geq \overline{BetP(\omega_{q_P})} \geq \cdots \geq \overline{BetP(\omega_{q_{|\Omega|}})}$$

- Select the P clusters associated with the P highest pignistic values

➔ New frame of discernment $\Omega' \subset \Omega$ where $|\Omega'| = P$

$$\Omega' = \{\omega_{q_i}, \text{with } i = 1, \ldots, P \text{ and } \omega_{q_i} \in \Omega\}$$

- New decision rule

$$\mathcal{R}_*(X_i) = \arg \max_{\omega_j \in \Omega'} BetP_{X_i}(\omega_j)$$

98

Evidential quantization algorithm

- Aim: to obtain P clusters
- 4 possible cases at the end of the decision step
  1. The number of clusters > P ➔ we continue
  2. The number of clusters = P ➔ we finish

  } No problem

  3. The number of clusters < P
  4. The partition is stable but the number of clusters > P

  } **Problem !!**

- Case 4 : our proposition
  - Idem than case 3 without backward step
  - Find the best P clusters among the $|\Omega|$ clusters: the **R_* rule**

Evaluation of the proposed algorithm

- Qualitative evaluation: the quantized image should preserve the visual perception of the original one

- Quantitative criterion: Mean Square Error

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left((r_i - \hat{r_i})^2 + (g_i - \hat{g_i})^2 + (b_i - \hat{b_i})^2\right)$$

where : $\hat{r_i}, \hat{g_i}, \hat{b_i}$ are the color components of the cluster prototype associated to pixel having components r_i, g_i, b_i

Results

Original image
183525 colors



(a) original image (b) $K = 256$ (c) $K = 128$

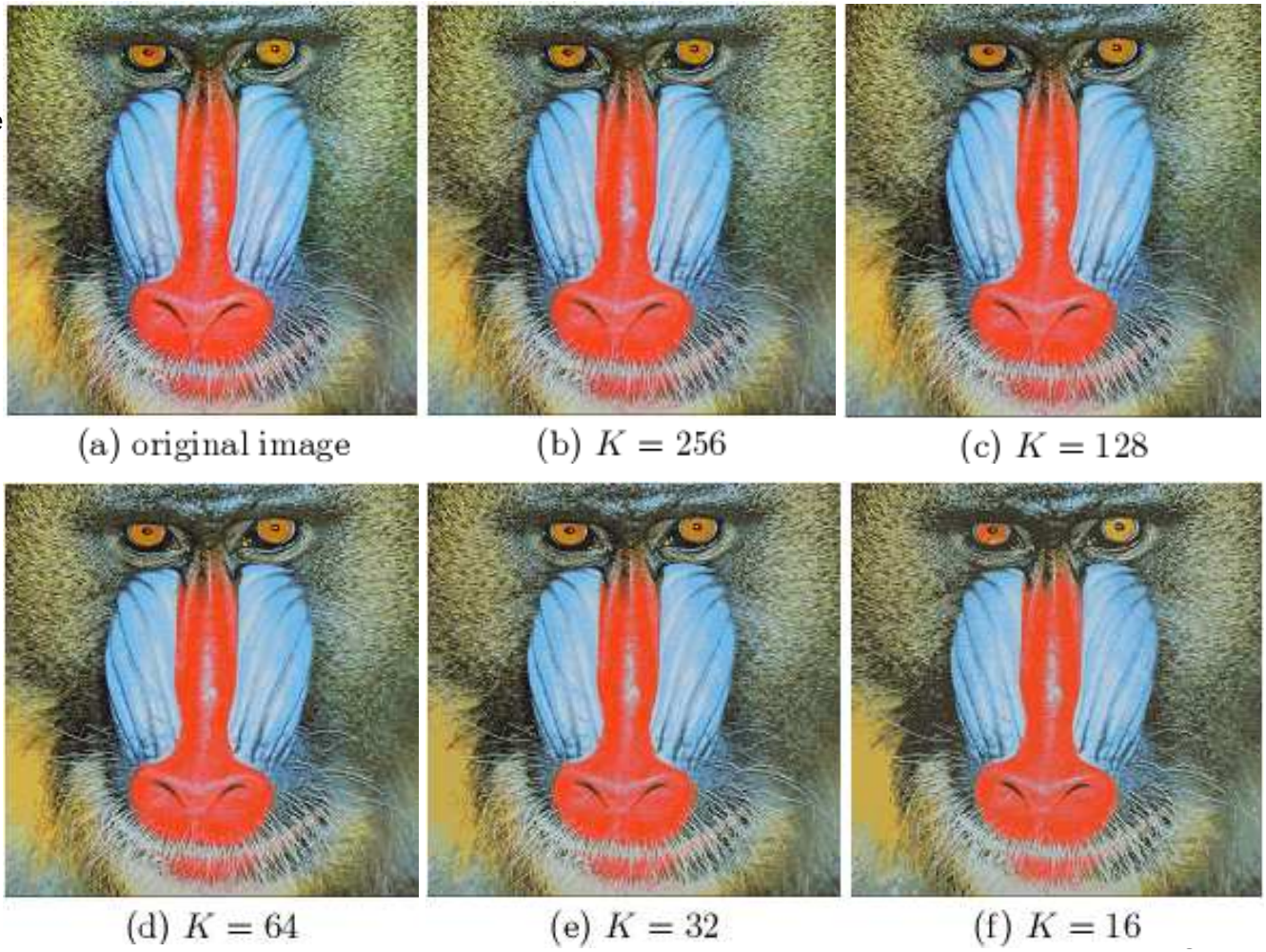


(d) $K = 64$ (e) $K = 32$ (f) $K = 16$

101

Results

Original image
230427 colors



(a) original image (b) $K = 256$ (c) $K = 128$

(d) $K = 64$ (e) $K = 32$ (f) $K = 16$

Quantitative criterion: MSE

Table 1: Quantization results - MSE criterion

	P	RWM-cut [9]	Ing [14]	Credal-Q
Baboon	16	804.570	779.43	681.93
	32	568.05	449.52	416.10
	64	360.60	282.33	268.33
	128	229.17	182.13	177.58
	256	155.70	117.63	127.26
Lena	16	307.71	240.27	228.93
	32	171.48	150.36	124.73
	64	106.32	92.55	78.45
	128	71.37	59.08	53.83
	256	50.01	40.98	34.64
Peppers	16	538.86	506.10	441.11
	32	225.22	277.20	257.52
	64	211.68	160.74	156.15
	128	139.65	101.43	91.55
	256	88.89	64.71	61.41

Credal quantization:

- best MSE values
- performance increases when the number of colors is small

Adaptative clustering algorithm

[14] Kuo-Chin Fan Ing-Sheen Hsieh. An adaptive clustering algorithm for color quantization. *Pattern Recognition Letters*, 21:337–346, 2000.

Splitting algorithm

[9] C.K. Yang and W.H. Tsai. Color image compression using quantization, thresholding, and edge detection techniques all based on the moment-preserving principle. *Pattern Recognition Letters*, 19(2):205–215, 1998.

BFT
applied to 3D computer generated images

Topics :

- *Shape matching*
- *Indexing*

3D-matching method of non-rigid and partially similar models using curve analysis

References

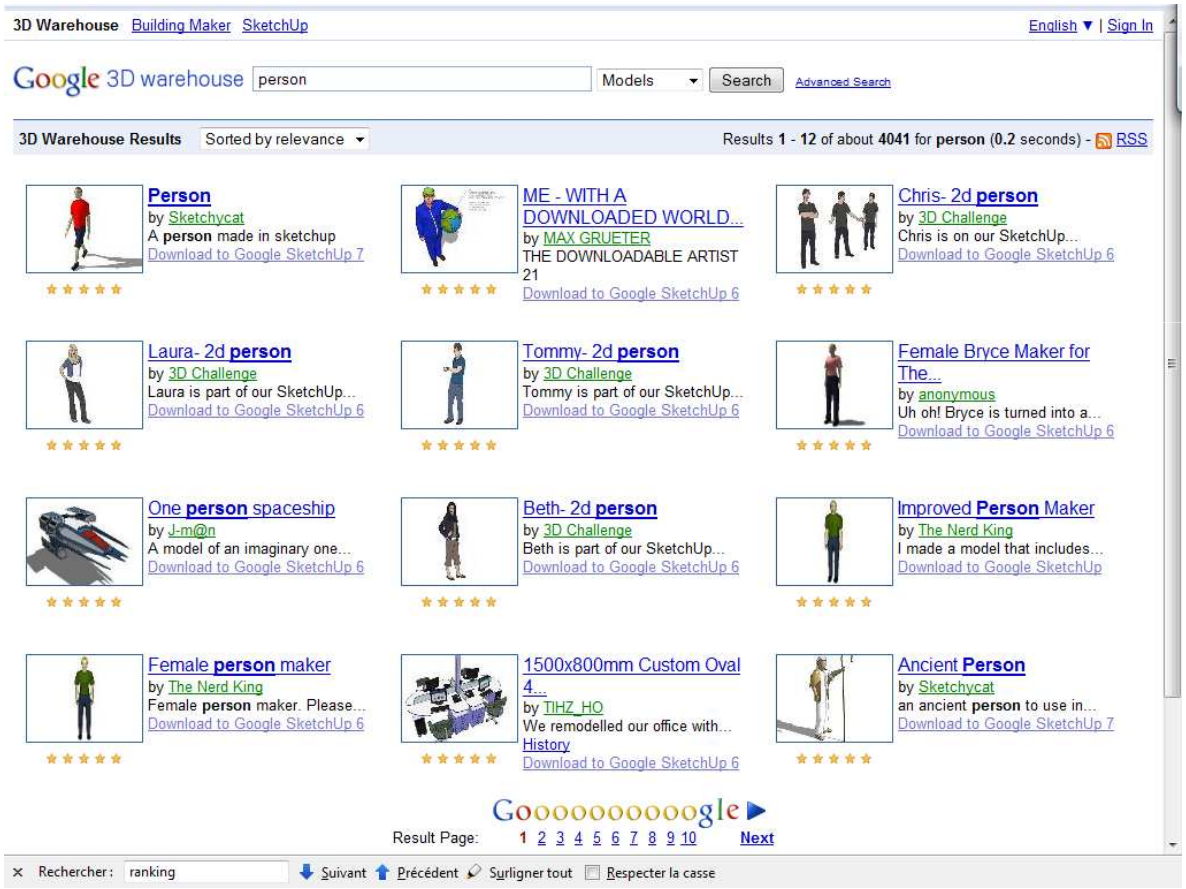
H. Tabia, M. Daoudi, J.-P. Vandeborre and O. Colot, "3D-matching method of non-rigid and partially similar models using curve analysis", *IEEE Trans. on Pattern Analysis and Machine Intelligence*, **33**(4), 2011, pp. 852-858.

H. Tabia, M. Daoudi, J.-P. Vandeborre and O. Colot,"Local Visual Patch for 3D Shape Retrieval", *International Workshop on 3D Object Retrieval (in conjunction with ACM Multimedia 2010)*, Firenze, 2010.

Outline

- Motivation
- Feature point extraction
- Local patch description
- 3D-shape matching using belief function
- Results on Shrec07, Tosca and Sumner Datasets
- Conclusion

Motivation

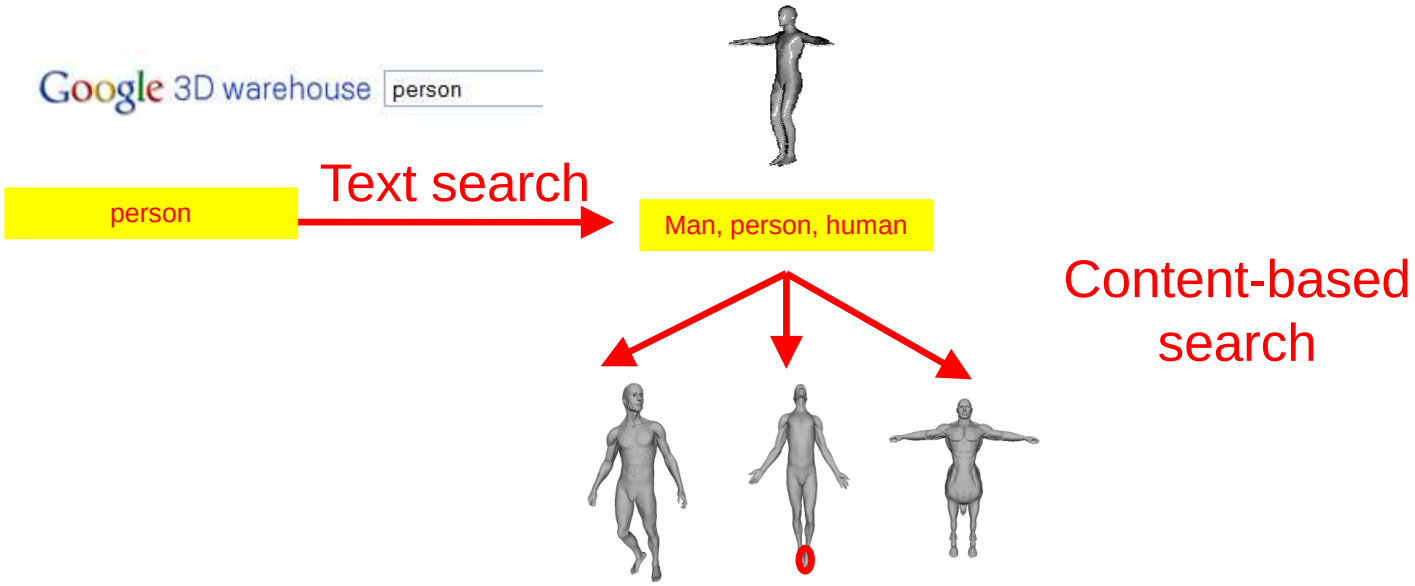


107

Objective:

Content-based search

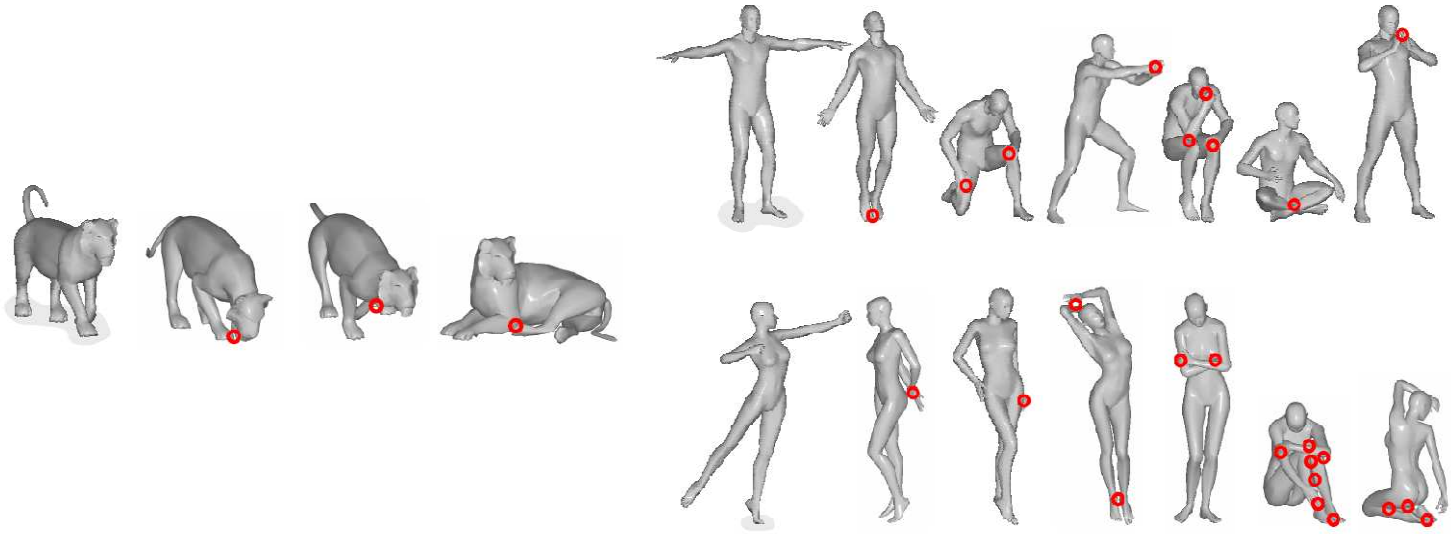
Analyzing deformations of surfaces



- Which parametrization and representation of surfaces ?
- How to compute the dissimilarity between shapes ?

SHREC07, Tosca[1] and Sumner[2] Datasets

- Examples of 3D objects



1 http://tosca.cs.technion.ac.il/

2 http://people.csail.mit.edu/sumner/research/deftransfer/

3 http://partial.ge.imati.cnr.it/

○ = topology change

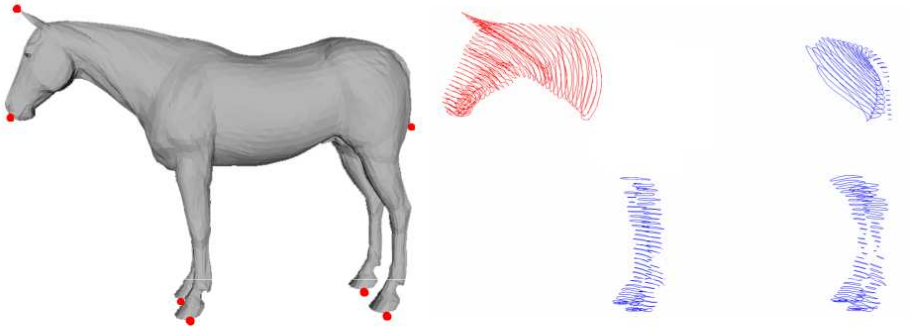
Previous works on 3D object retrieval

Most of the works on 3D retrieval can be categorized in 2 categories:

- Non-rigid: view based methods, global descriptors…
- Rigid: Graphs, local descriptors…
- Bag-of-Features (BoF)
  - Ohbuchi *et al*. SMI 2008,
    - 2D approach, SIFT,
    - MSB, McGill Benchmarks
  - Lian *et al*. SMI 2010,
    - 2D approach, SIFT
    - PSB, NSB, ESB, McGill Benchmarks
  - Bronstein and Kokkinos CVPR 2010,
    - Heat Kernel Signature
    - Shape Google Dataset, Tosca

Proposed approach

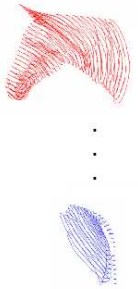
1) Feature Detection



2) Patch representation

3) Matching using Belief Function techniques

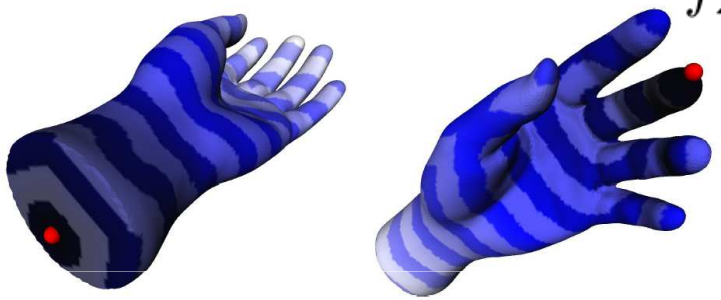




	O_1	O_2	$\cdots$	O_M	Ω
P_1	$m_{P_1}(O_1)$	$m_{P_1}(O_2)$	$\cdots$	$m_{P_1}(O_M)$	$m_{P_1}(\Omega)$
P_2	$m_{P_2}(O_1)$	$m_{P_2}(O_2)$	$\cdots$	$m_{P_2}(O_M)$	$m_{P_2}(\Omega)$
$\vdots$					$\vdots$
P_N	$m_{P_N}(O_1)$	$m_{P_N}(O_2)$	$\cdots$	$m_{P_N}(O_M)$	$m_{P_N}(\Omega)$

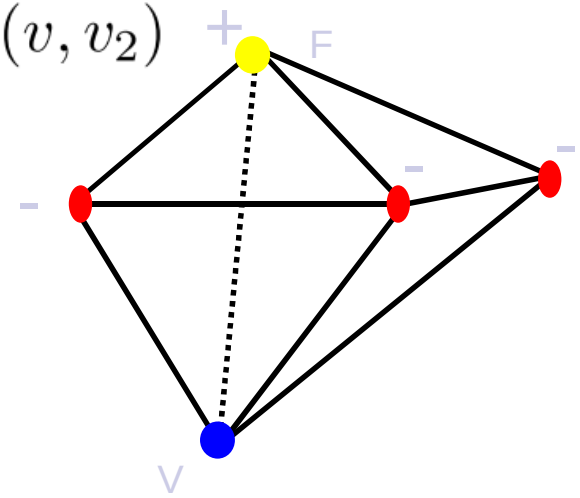
Feature point extraction

$f_2(v) = d(v, v_2)$



$f_1(v) = d(v, v_1)$

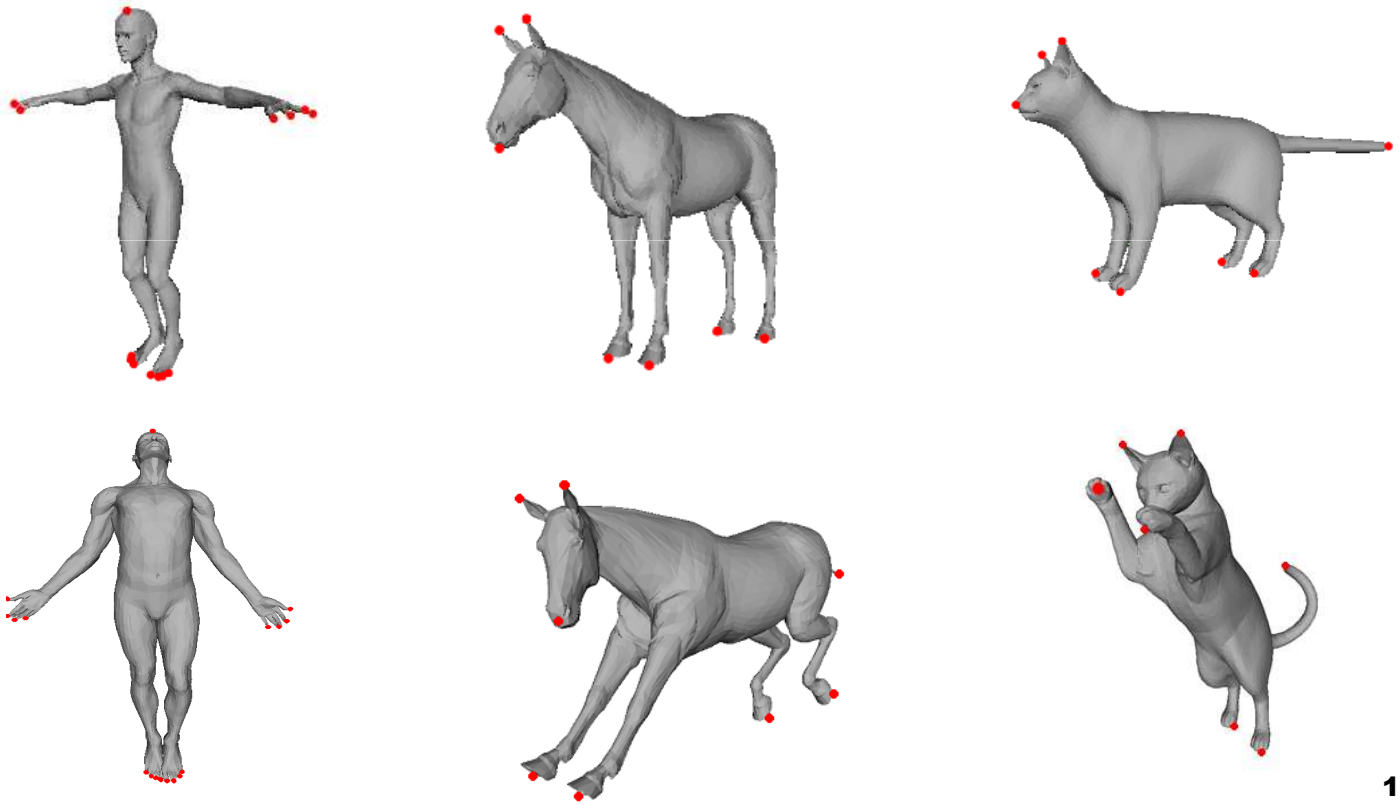




Example

- [Tierny *et al.*, CGF2009]

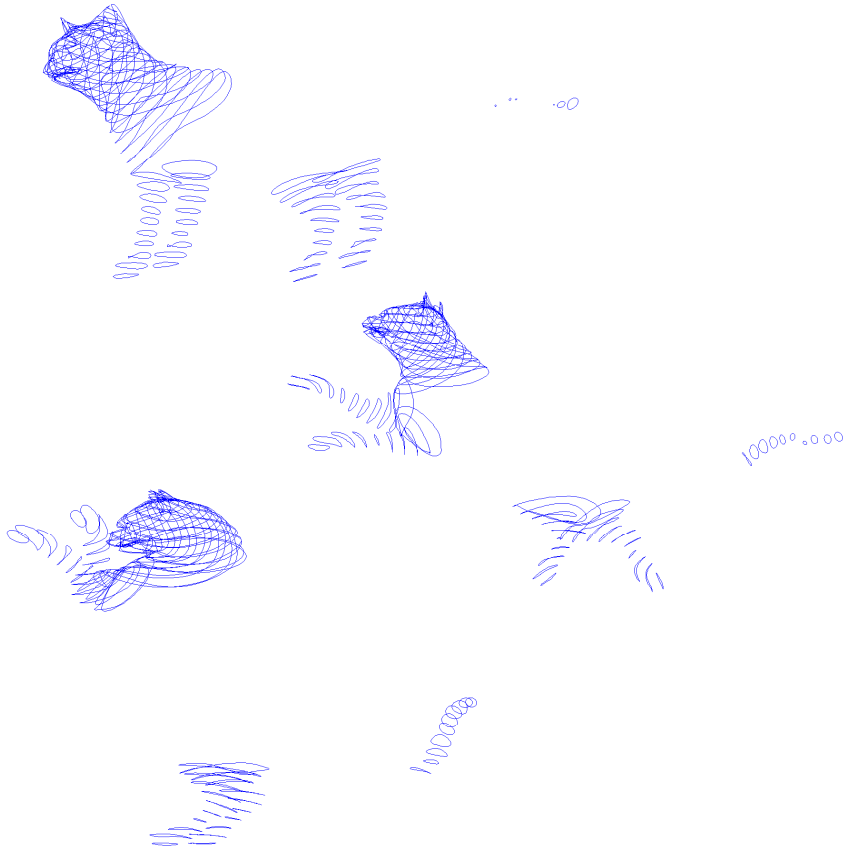
Feature point extraction



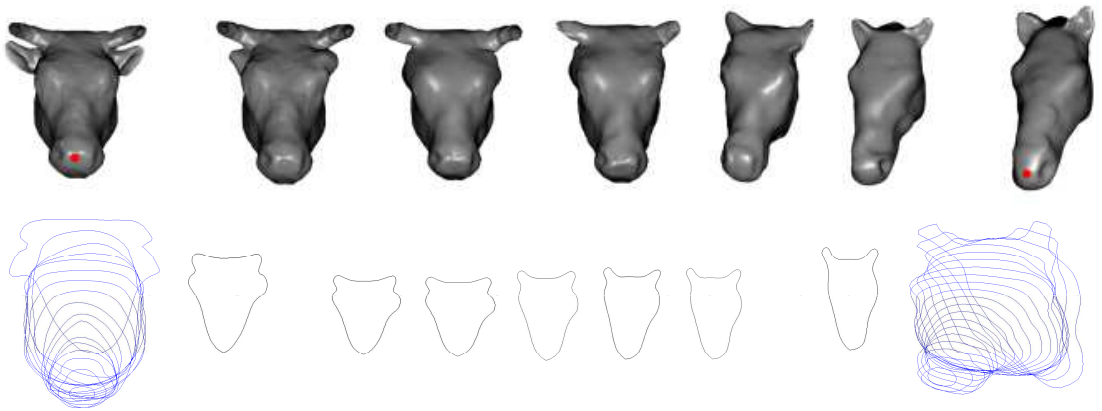
Local patch description

- Surfaces = represented by 3D-curves extracted around feature points.
- 3D object : set of patches
- Patches = a collection of closed curves
- Patches are compared by analyzing their curves.

Local patch description



Distance between Patches



The shapes of any two parts are compared by using their corresponding curves:

$$D(P_1, P_2) = \int_0^L d(c_\lambda^1, c_\lambda^2) d\lambda.$$

3D-Shape matching using belief functions





	O_1	O_2	$\cdots$	O_M	Ω
P_1	$m_{P_1}(O_1)$	$m_{P_1}(O_2)$	$\cdots$	$m_{P_1}(O_M)$	$m_{P_1}(\Omega)$
P_2	$m_{P_2}(O_1)$	$m_{P_2}(O_2)$	$\cdots$	$m_{P_2}(O_M)$	$m_{P_2}(\Omega)$
$\vdots$					$\vdots$
P_N	$m_{P_N}(O_1)$	$m_{P_N}(O_2)$	$\cdots$	$m_{P_N}(O_M)$	$m_{P_N}(\Omega)$

Belief functions

Confidence coefficient
(based on partial similarity
of object [Bronstein, 2008])

Distance between P_i and the closest one in O_j

$$m_{P_i}(O_j) = \mu(P_i) \cdot \frac{1 - D_1(P_i, O_j)}{\sum_{l=1}^{M}(1 - D_1(P_i, O_l))}$$

$$m_{P_i}(\Omega) = 1 - \mu(P_i)$$

With:

$$D_1(P_i, O_j) = \min_{k, P_k \subset O_j} (D(P, P_k))$$

$$\mu(P_i) = exp(-npartiality(P_i)^2)$$

Where the $npartiality$ depends on the area of the 3D part

$$npartiality(P_i) = \frac{area(Q) - area(P_i)}{area(Q)}$$

Algorithm

Algorithm 1. 3D-shape search algorithm

Given a 3D-object query Q.

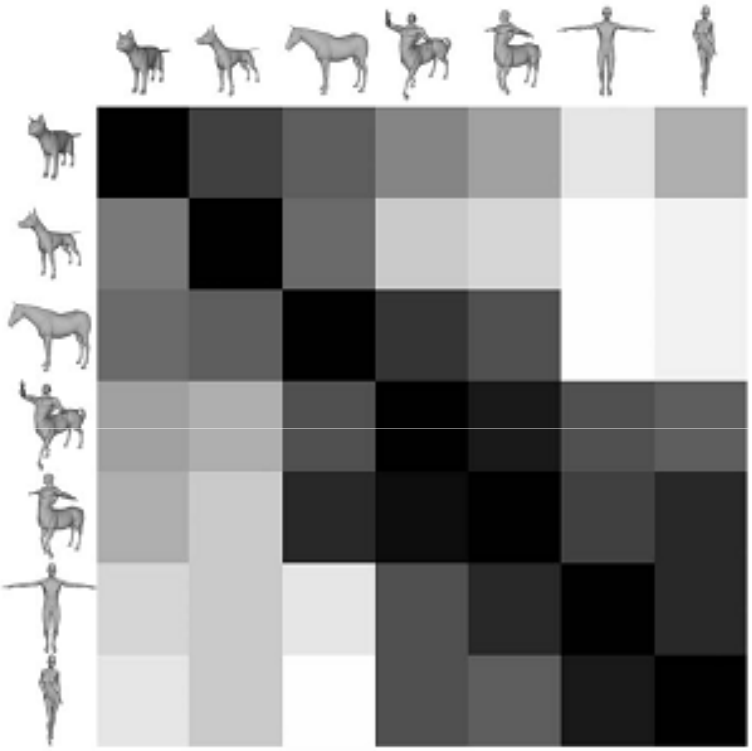
1: *Extract a set of N feature points V_i from Q.*
2: **for** *each feature point V_i where $i = 1, \ldots, N$* **do**
3: *Extract a set of closed curves (i.e., part P_i).*
4: *Compute the distance between P_i and all objects in Ω*
5: *Set a BBA value for all the objects $m_{P_i}(O_j)$*
6: **end for**
7: *Combine all BBAs m_{P_i} into a new BBA m_Q*
8: *Compute the pignistic probability induced by m_Q*
9: *Display 3D objects in the order according to the pignistic probability.*

Final matching

- When all patches P_i of the query Q are modeled by their corresponding mass functions, Dempster's rule of combination is applied in order to get a mass function which measures the amount of belief committed to the assumption: « Q is similar to O_j ».

- Decision making: Pignistic probability
- Retrieval: objects are sorted according to the pignistic probability values.

Shape retrieval results



Matrix of pairwise distances between seven 3D objects

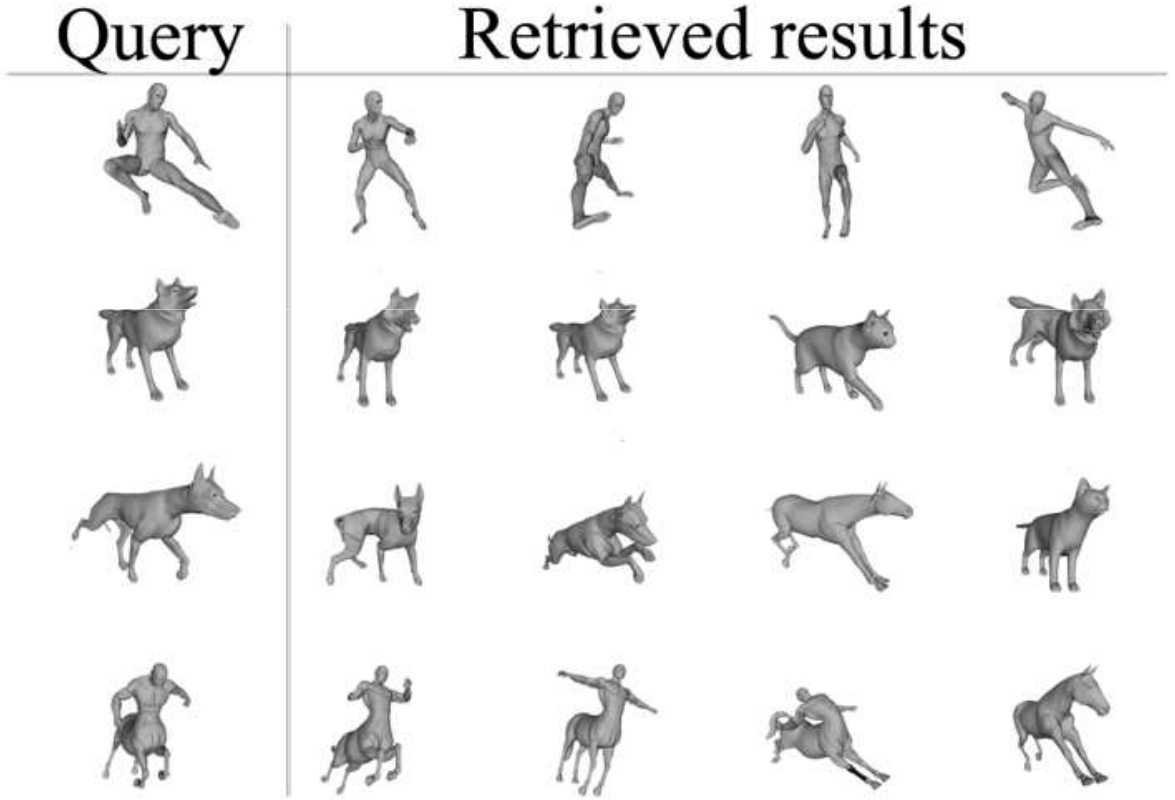


Low (objects are similar)

High (objects are different)

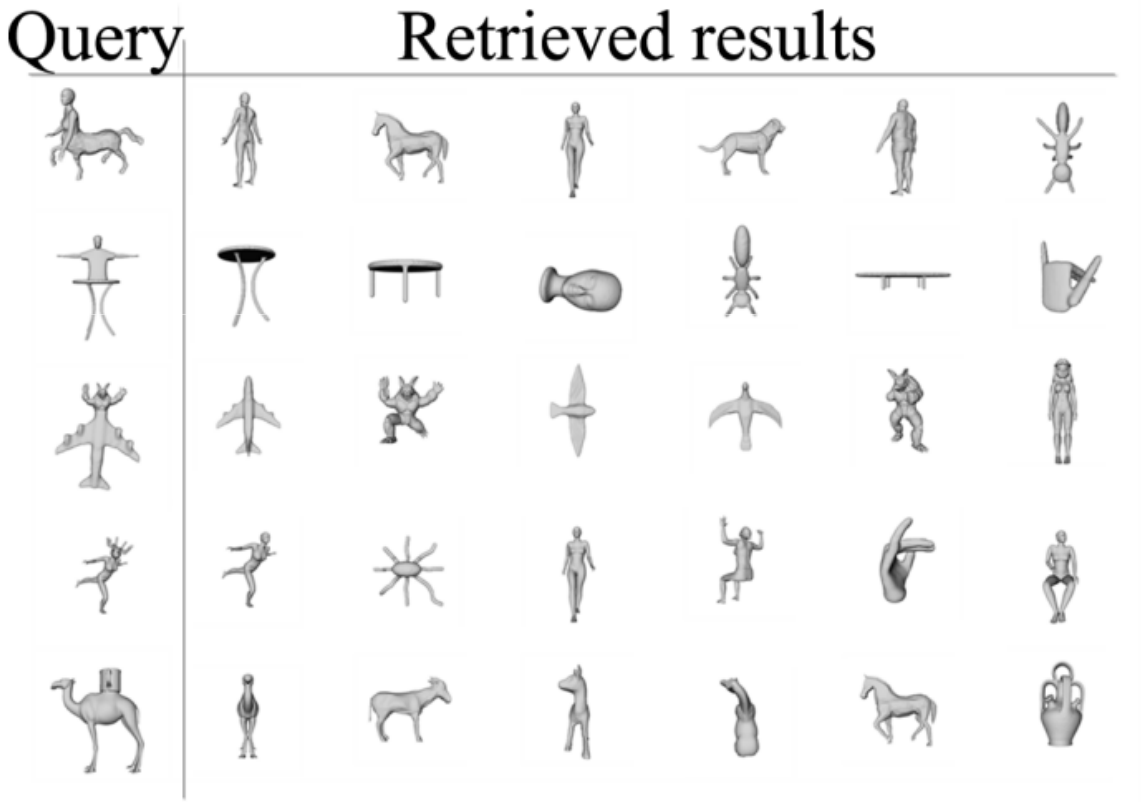
121

Shape retrieval results



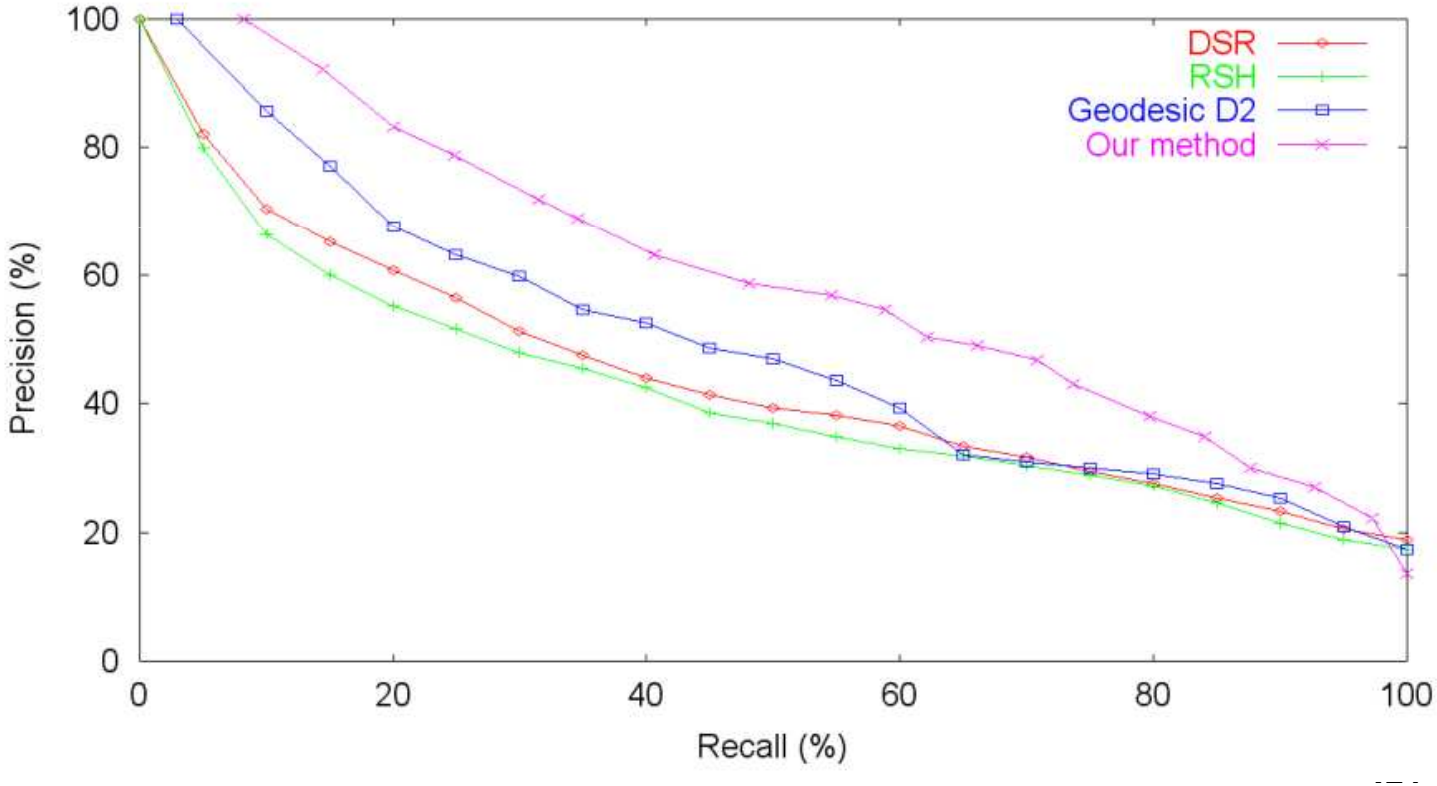
122

Shape retrieval results



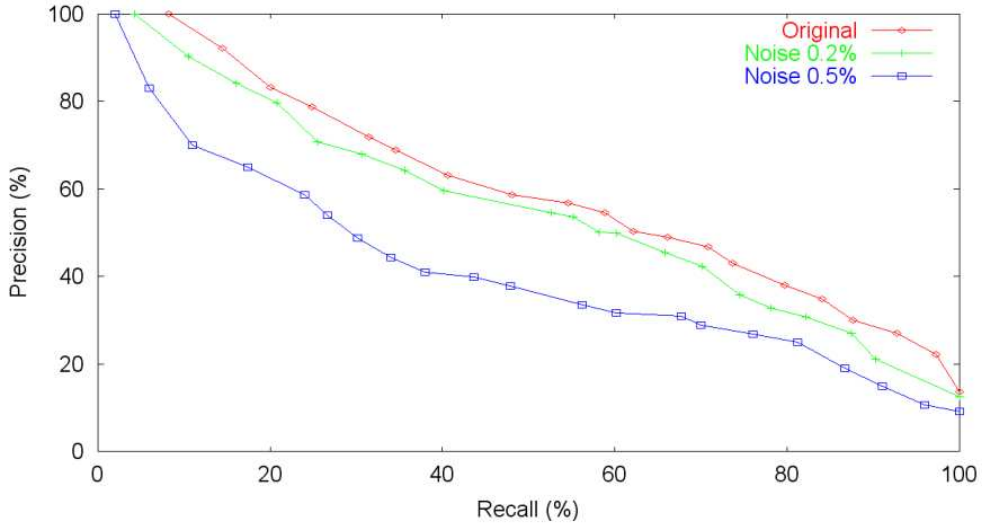
Results: comparison with some well-known methods

Comparison on TOSCA database



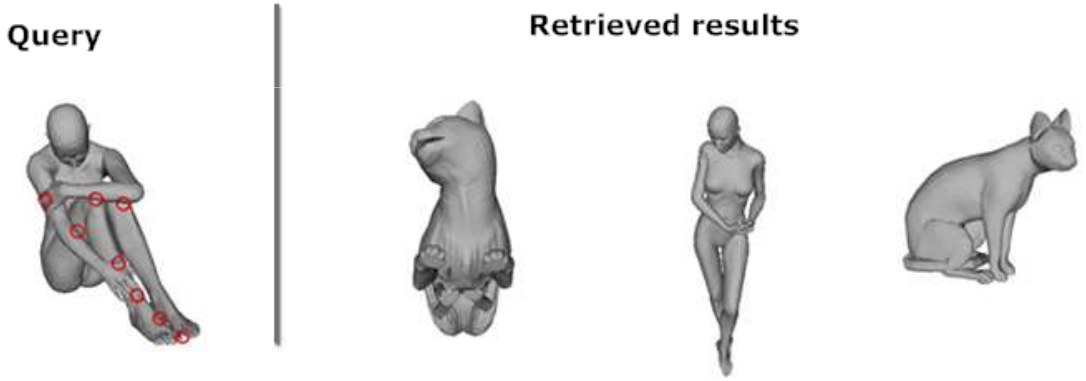
Results: Robustness to query noises





Remark

- Limitation (topological changes)



That's all folks!

