Complex analysis of historical documents

Application to lettrines

http://NAVIDOMASS.univ-lr.fr

Mickaël Coustaty

Supervisor: Prof. Jean-Marc Ogier

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Searching for an image

Searching for an image is very popular

- To retrieve similar information
  - Retrieve the name of a visited place
  - Retrieve the name of a person
- To search for specific images
  - To compare images
  - To find the author
  - To illustrate a presentation
- Made using internet research engines (Google, Yahoo, Flickr, ..)

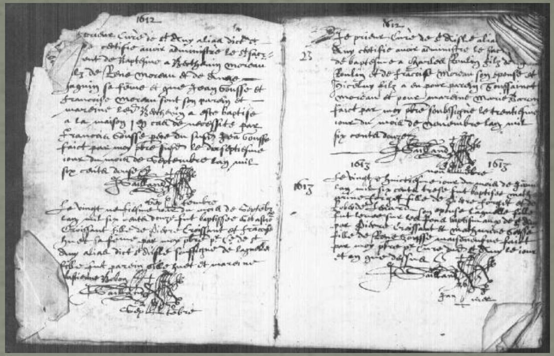
Searching for a document

- Has the same goals
  - Retrieve a similar/specific information

- Used in many domains and organizations (EDM)
  - Medecine
  - Companies
  - Libraries
- Many digitizating process are observed
  - Reduces costs
  - Speeds up treatments and frees up time
  - Makes the documents more accessible

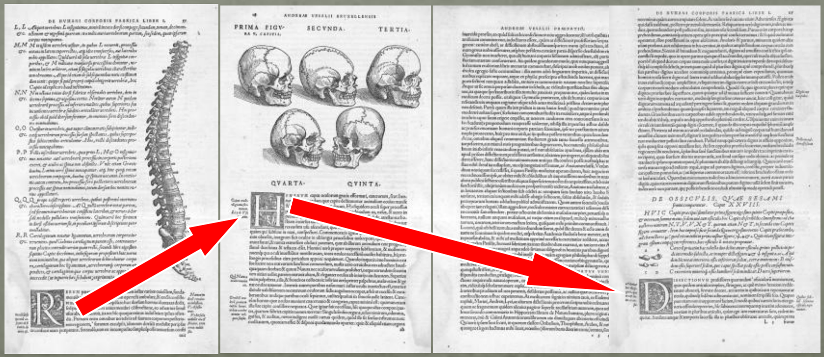
Searching for historical documents ?

- To preserve their content
  - from degradations



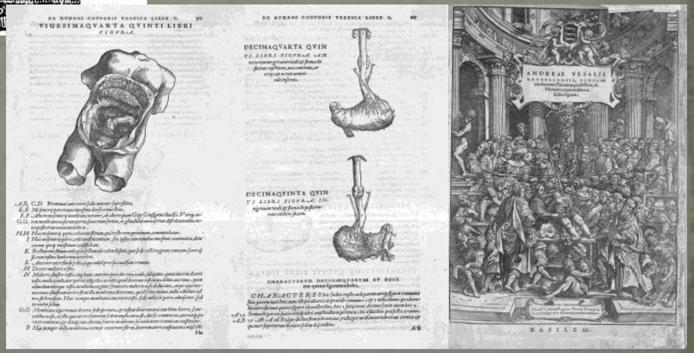
- To make them available
  - Online consultation
  - Simultaneous consultation

- To navigate / retrieve similar images
  - To date them
  - To identify printer
  - …



Stakes related to historical documents

- Cultural Heritage
  - Memory of our societies
  - A huge amount of documents
- Commitment of many digitization campaign (in Europe and in the world)
  - Google Book, Europeana, Impact, PIxL, ….



Historical documents digitization issues

- Need to deal with the problem of
  - Sharing documents
  - Navigation into these databases
- Need to analyze historical documents
  - By characterizing their content
  - To Index them
  - To propose navigation services
- Some historical documents features
  - Irregular structure
  - Noisy images
  - Huge amount of documents
  - …
- NaviDoMass Project
  - Aims at developing services to navigate into these document image databases

Navidomass project

* Project leader

Institut de Recherche en Informatique et Systèmes Aléatoires (Rennes)

Laboratoire d'Informatique de Traitement de l'Information (Rouen)

Laboratoire d'informatique image et interaction (La Rochelle) *

Centre d'Etude Supérieures de la Renaissance (Tours)

Labo d'informatique de Paris Descartes (Paris)

Laboratoire Lorrain de Recherche en Informatique et ses Applications (Nancy)

Laboratoire Informatique (Tours)

Computer science			This thesis	Humanities
Collection modelling, Structure analysis, Preprocess images	**Information spotting graphical - text**	**Feature selection, Define metrics and Feature space structuring**	Human-Machine Interaction relevance feedback	Books digitization groundtruth
LI, IRISA, LITIS, L3i, CESR	**LORIA, L3i, LIPADE, LI, LITIS, IRISA, CESR**	**LITIS-LORIA-LIPADE-L3i**	LI - L3i - LORIA - CRIP-CESR	CESR

Specificities of our graphic images

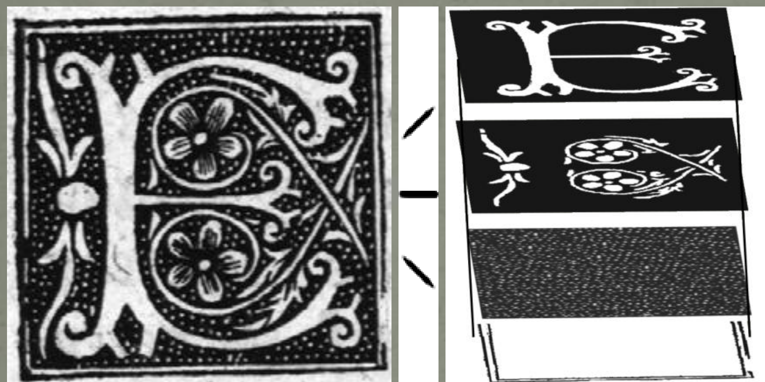
- Images from the XVth and XVIth
  - Start of printing
    - Images degraded by time
  - Printed using wood stamp
    - Images in black and white
    - Composed of strokes

- Lettrines !
  - A letter with decoration
  - Many semantic information

Lettrines – 2 points of view

Complex images

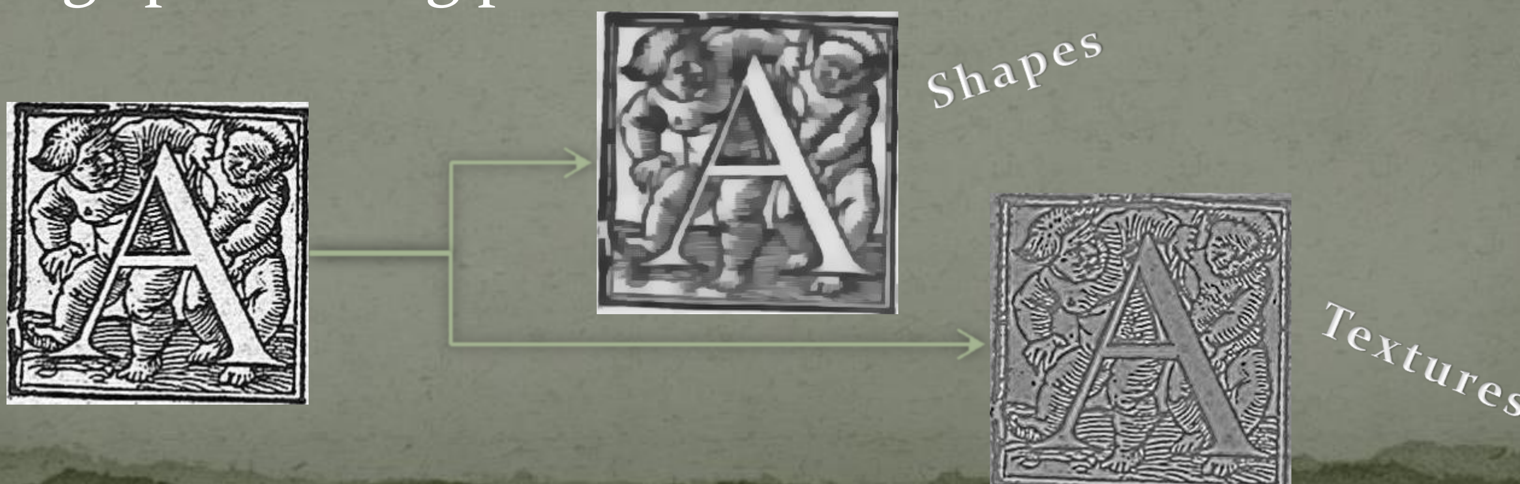
- Historian point of view



  - Letter
  - Pattern
  - Background
  - Frame

Semantic Gap

- Image processing point of view



How to search for similar images ?

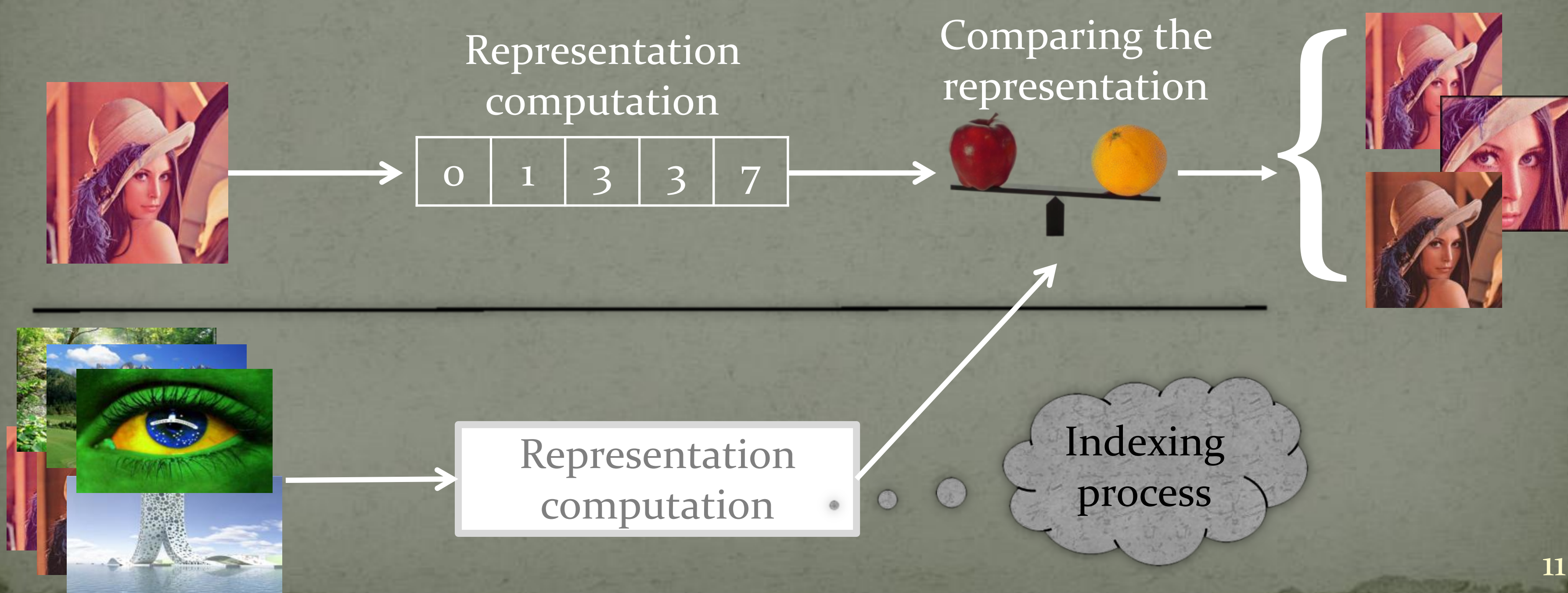
- Using query by example

- Using specific keywords (from expert knowledge)

La Rochelle
+ Old harbour
+ Two towers

Computer science image description

- Keywords annotation
  - Manual
  - Automatic
- Content-Based Image Retrieval



State of the art - discussion

	Keywords	CBIR
Advantages	• Easy to implement • Fast to implement	• Many works • Works quite well for frequent images
Drawbacks	• Difficulty to extract keywords • Polysemy • Langage dependant • Subjectivity	• How to extract RoI or keypoints ? • Which features ? • A picture is worth a thousand words

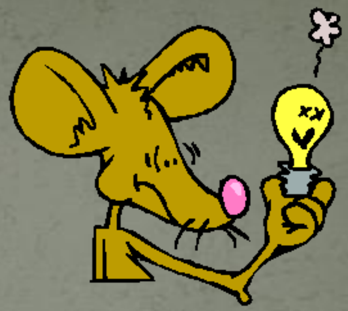
Ideal historical documents search engine *Requirements*

- Must be able to deal with
  - Low-level knowledge (image processing features)
  - High-level Knowledge (historian's keywords)

- Must be customizable
  - To be adapted to different use-cases
  - To be specified to images (damaged, weakly structured, …)

- Outsource knowledge of the system
  - To be able to easily control the steps of the process

Idea



Make a system which allows:

Low level features

Query by Example

And

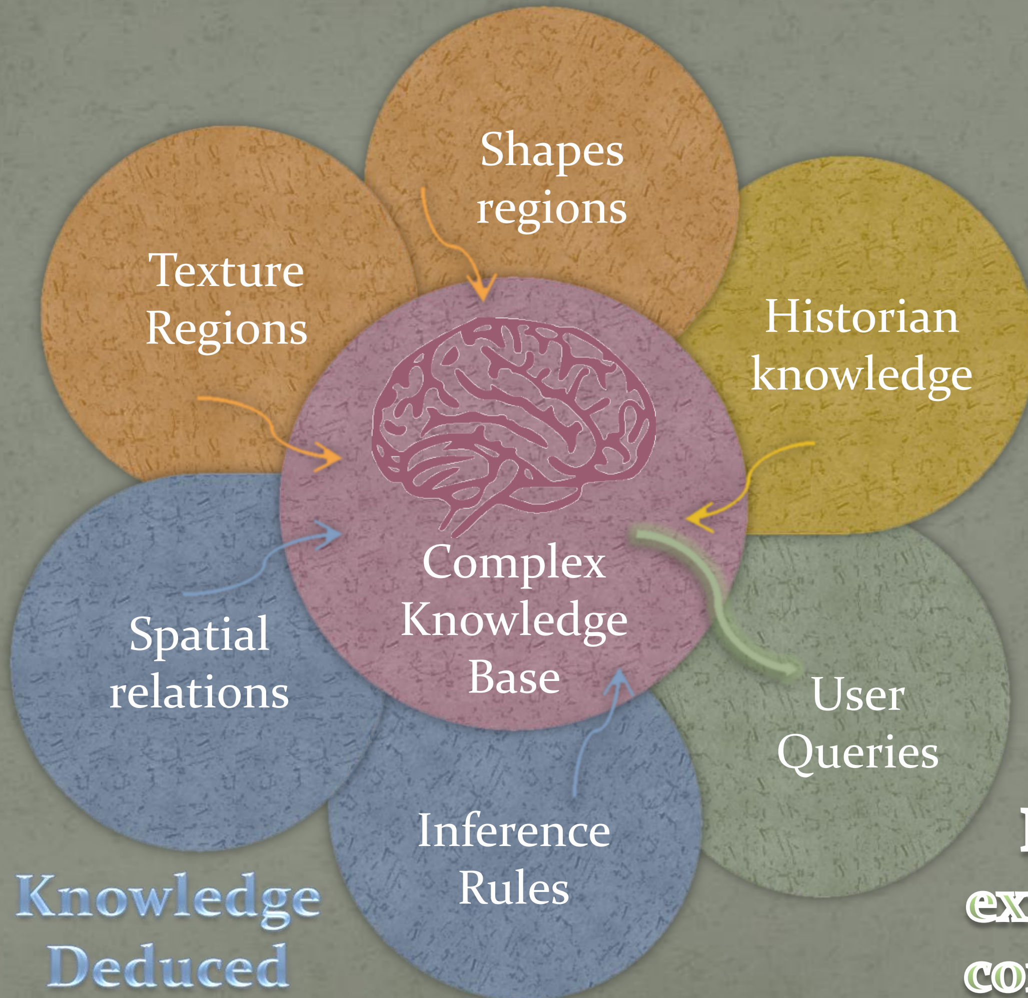
Query using keywords from expert domains

High level features

Complex Knowledge Management

Image Processing knowledge

Low level features



Domain Experts Knowledge

High level features

Mid-level features

Knowledge Deduced Automatically

Information extraction using complex queries

Outlines of the proposed approach

Two levels of analysis

I. Automatic and complex image analysis
- Extracting regions of interest
  - Describing their contents
  - Describing their relationships
- Measuring their similarities

II. Knowledge management
- To represent historian's knowledge
- To represent image processing's knowledge
- To reduce the semantic gap between these domains

Outlines of image analysis part

- Image simplification (different layers of information)
  - Brief state of the art
  - Method adopted

- Complex Image description adapted to each layer
  - Shape layer
    - Brief state of the art
    - Proposed signatures
  - Texture layer
    - Brief state of the art
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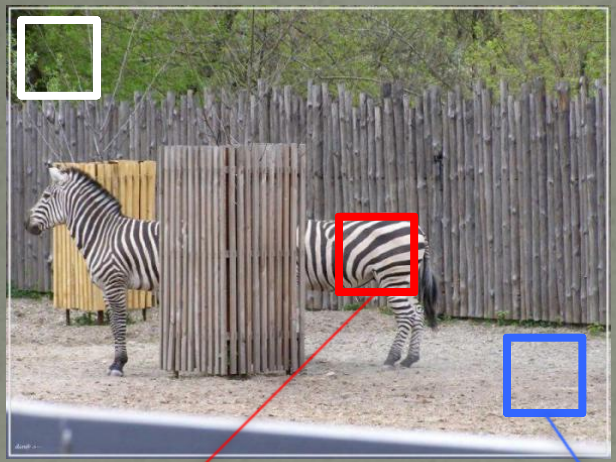
Image simplification – State of the art

- Consists in separating image content
- Separation relies on different types of information
  - Uniformity
  - Texture
  - Color
  - …
- Local vs Global

Image simplification - Local approaches



Textured

Homogeneous

- Density criteria
- Frequency criteria
- Saliency criteria

Image simplification - Global approaches

- Consist in applying a global filter on the image
  - Analysis based on the frequency domain

  - Many existing approaches
    - Wold decomposition [Francos 93]
    - Wavelet [Mallat 99]
    - Zipf law decomposition [Pareti 08]
    - MCA [Dubois 10]
    - …

- Method adopted: Meyer decomposition [Aujol 05]
  - *Linked with historian decomposition*

Image simplification –Method adopted

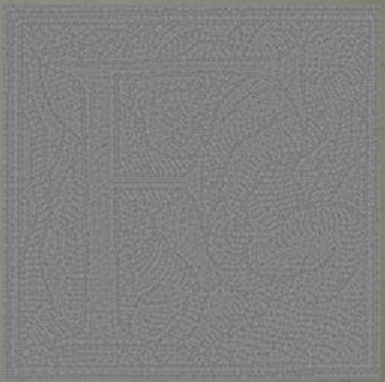
- Meyer's Decomposition

Original image

- Why ?
  - Allows image simplification
  - Similar to experts' decomposition
- How does it work ?
  - Image content separated in 3 layers

U : shape's layer

V : texture's layer

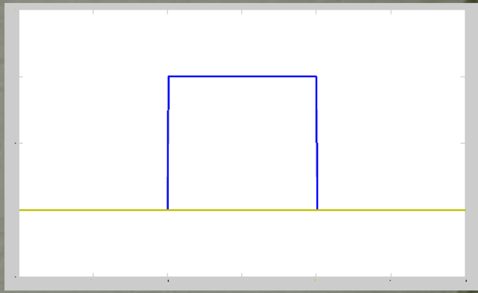


W : noise

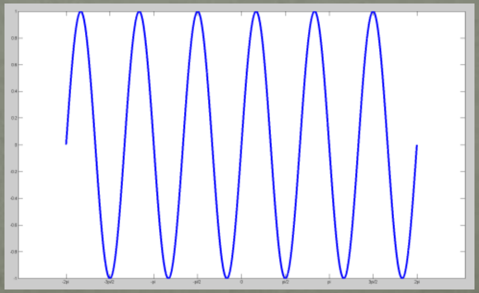
Meyer’s decomposition - principles

Functional Minimization

$$\inf_{(u,v,w)\in X^3}(F(u,v,w)) = J(u) + J*\left(\frac{v}{\mu}\right) + B\left(\frac{w}{\lambda}\right) + \frac{1}{2\alpha}\|f-u-v-w\|_{L^2}$$



- U : Geometrical component
  - To get functions with a finite total variation
  - Correspond non-oscillating functions
  - Keep boundaries
- V : Texture component
  - To get the oscillating functions
  - Correspond to oscillating to fast-oscillating functions with a mean equal to 0
  - Obtained why the Meyer’s norm (can be seen as an integral) [Meyo1]



- W : Noise component
  - All that does not belong to the two first layers
  - W = f – (U + V)
  - Denoise the image

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Shapes descriptors – State of the art

- Issuing from PR and CV communities

- Summarize the content of an image using statistical/structural description

- Four main categories
  - Invariant moments [Hu 62], [Zernike 38]
  - Transformation-based approach [Bracewell 00] ,[Adam 00], [Tabbone 06]
  - Multi-resolution based representation [Mallat 99], [Bui 99], [Shen 99]
  - Structural signatures [Etemadi 91], Matsakis 99], [Wendling 02], [Llados 01]

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Structural + Statistical

  - Texture layer
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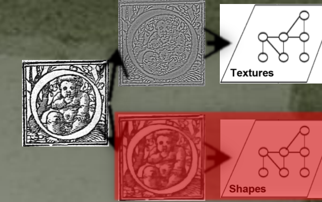
Shapes Layer – Segmentation

Zipf's Law in Four steps [Zipf 49][Pareti 08]



Shapes' layer

Using
3-Means

1
Simplified image

2
Pattern retrieval
+
Count

2	2	2
2	2	2
2	2	2

42626 occurences

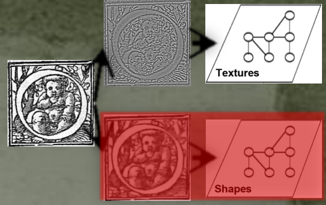
0	0	0
0	0	0
0	0	0

21227 occurences

3
Ranked patterns
+
Approximation

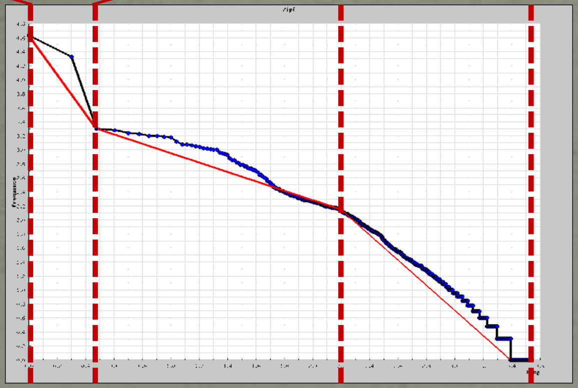
o
c
c
u
r
e
n
c
e
s

Each pattern



Shapes Layer – Segmentation
Zipf's Law fourth step - Pixel selection / Shapes extraction

Most frequent patterns



Set of patterns

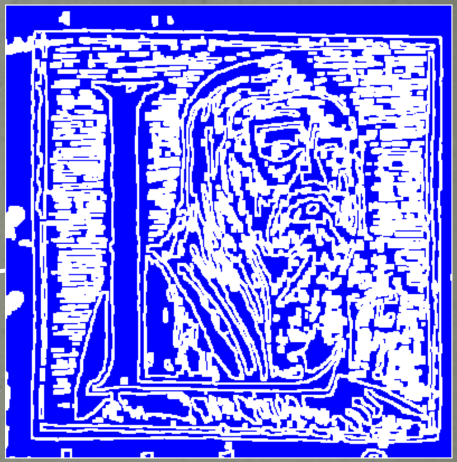
Nb of occurrence

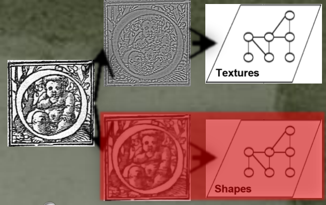
Layer 1

Layer 2

Layer 3

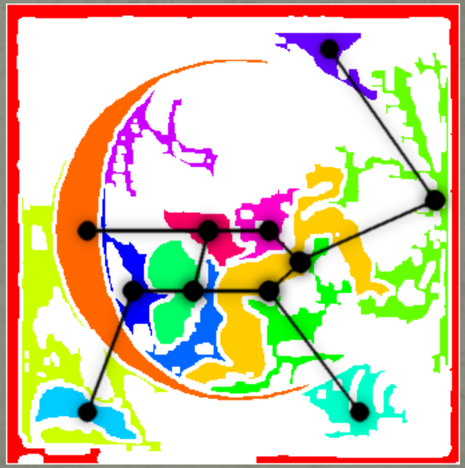
Pixels selection





Shapes layer – Structural description

Region selection based on their size

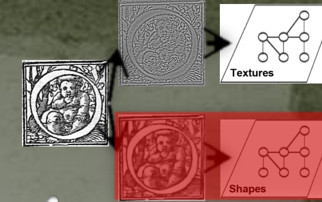


Neighbourhood Graph computation:

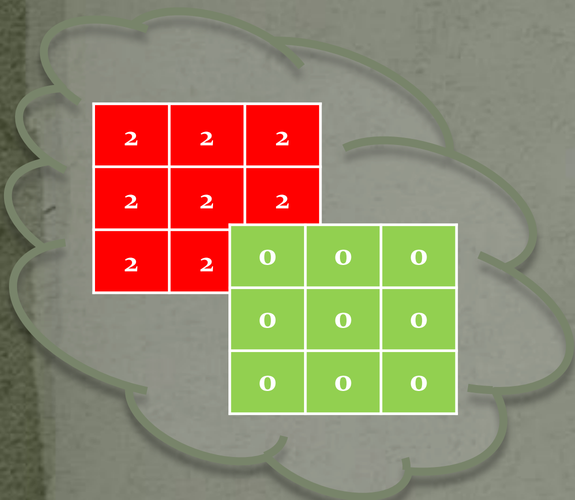
- Each node = a region
- Edges = distance between 2 regions

Similarity measure [Jouili 10]:

$$\gamma(n_i) = \left\{ \alpha_i,\ \theta(n_i),\ \{\theta(n_j)\}_{\forall ij \in E},\ \{\beta_{ij}\}_{\forall ij \in E} \right\}$$



Shapes layer – Statistical description



Set of patterns from an image

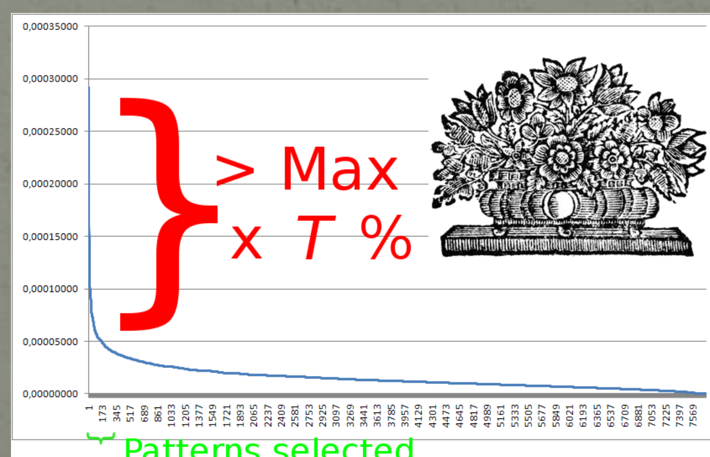
TF-IDF computation

TF = Term Frequency

Number of occurrences of pattern in an image

IDF = Inverse Document Frequency

Number of documents that contain the pattern



Similarity measure between images: $Sim_{i_1,i_2} = (1-(R_L * R_S)) * D_{Patt}$

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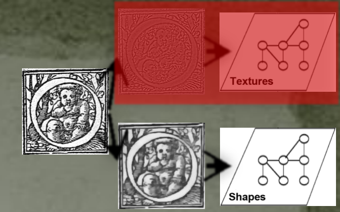

Texture description – state of the art

- 6 main categories of methods
  1. Kernel-based approaches
     - Stochastic approaches [Derin 87], [Komodakis 11]
  2. Model-based approaches
     - Markov models, AR, ARMA [Cheung 05]
  3. Descriptor-based approaches
     - Co-occurrence Matrix [Haralick 73]
  4. Methods using peculiar filters
     - Fourier, Gabor [Pham 07]
  5. Methods that rely on correlation and auto-correlation
     - [Rosenberger 99], [Uttama 08], [Journet 08]
  6. Methods that segment image into homogeneous areas
     - RLSA [Wong 82], XY-CUT [Journet 06], Voronoï [Fortune 86]

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    - Proposed signatures **Structural + Statistical**
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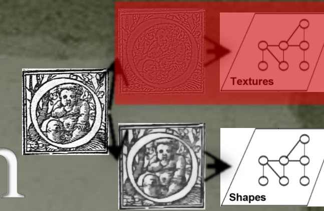
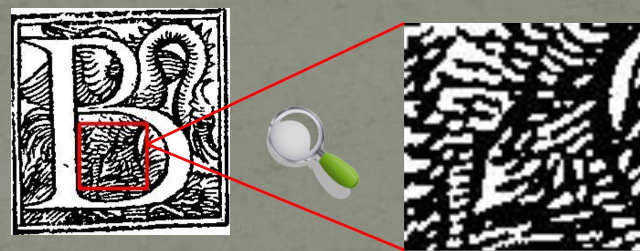
Stroke-based images

- Images composed of strokes
  - To mime shades of grey
  - To give relief to images
- Strokes correspond to
  - Semantic elements
    - Background
    - Shadows
    - Ground
    - …

Stroke-based texture segmentation



- Image printed using strokes



- Idea: the stroke becomes the basic information (instead of pixels)
  - Extract strokes

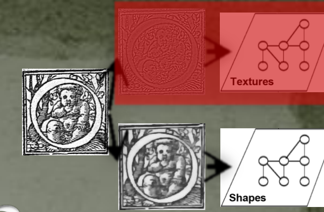
Original

Textures layer

Skeleton

  - Describe strokes with features vector

    < Length, Width, Complexity, Orientation, Freeman Code >



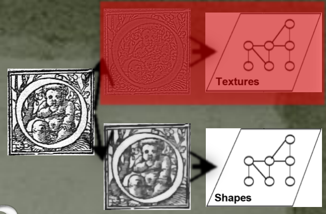
Texture layer – statistical description

- Bag of strokes

Clustering

of strokes

- Image description = Histogram of occurrences
- Similarity measure: $d = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2}$



Texture layer – structural description

- Strokes grouping
  - Neighbouring strokes with similar properties are merged

- Area selection
  - Region size
  - Number of strokes by region
- Neighbourhood Graph construction
  - A node = a region / Edge = distance between 2 regions
- Similarity measure [Jouili 10]

$$\gamma(n_i) = \left\{ \alpha_i,\ \theta(n_i),\ \{\theta(n_j)\}_{\forall ij \in E},\ \{\beta_{ij}\}_{\forall ij \in E} \right\}$$

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Image processing evaluation

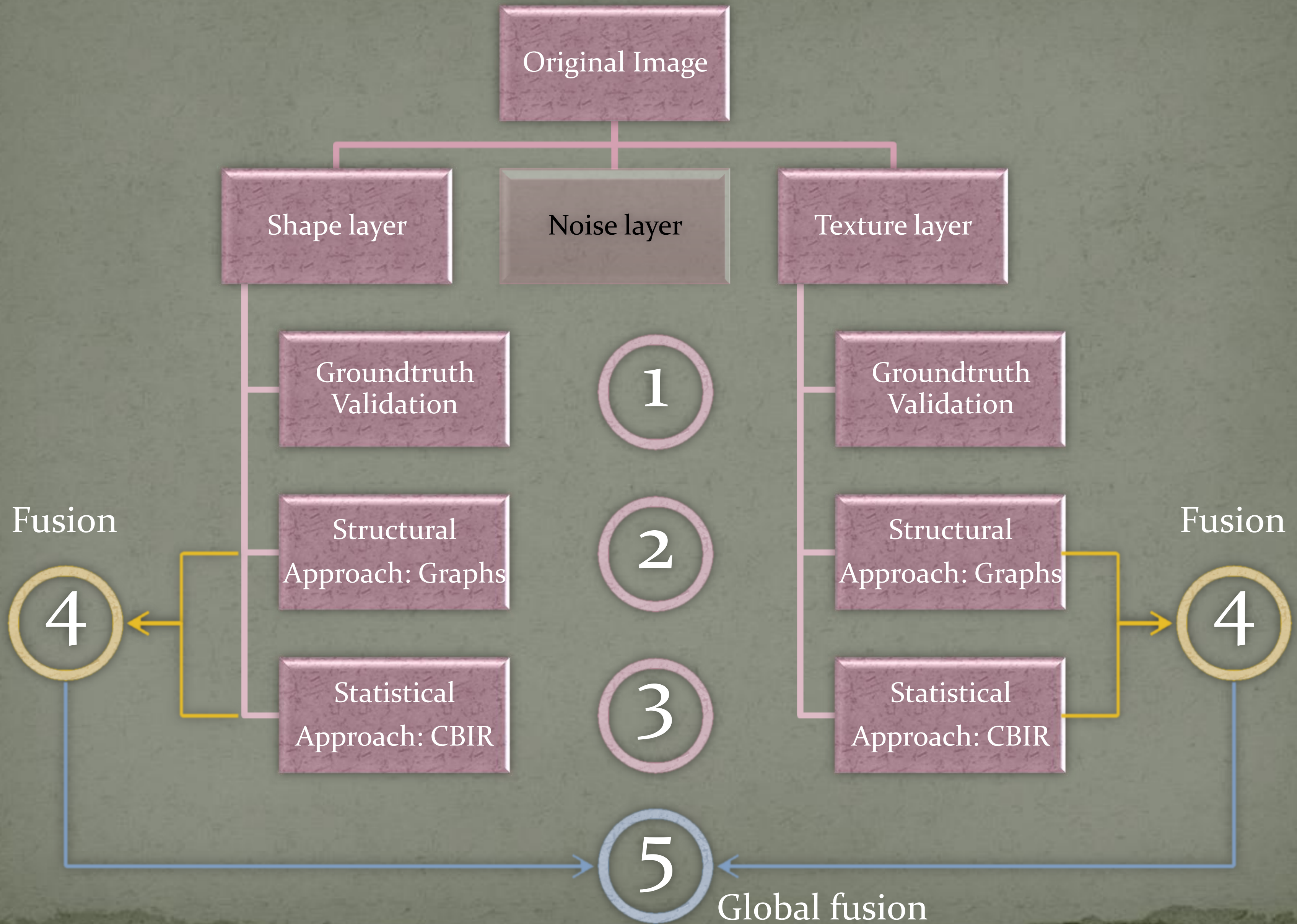
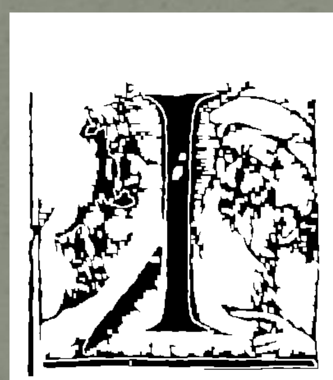


Image segmentation evaluation 1

Shapes

Original image

Groundtruth

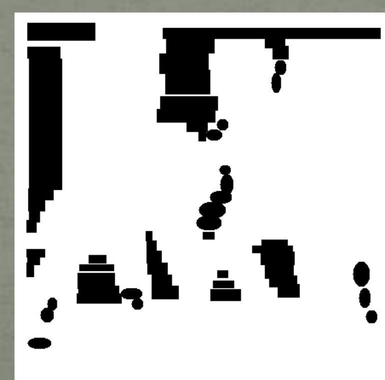


Automatically Extracted shapes

Textures

Original image

Extracted strokes



Groundtruth

Automatically Extracted strokes

Image segmentation evaluation 1

- **Recall**: % of regions from the groundtruth that contain automatically extracted elements (shapes or strokes)

- **Precision**: % of region from the groundtruth area that are overlapped by the automatically extracted region

Shapes

Recall	Precision
92.4 %	84.8 %

Textures

Recall	Precision
100 %	71.3 %

Image description evaluation 2 3

- Lettrine database
  - Database used by Pareti et al [Pareti 08]
  - 358 lettrines
  - Learning: 11% (10 images / style)
  - Recognition: 89% (318 images)

Style 1 Style 2 Style 3 Style 4

Structural

Image processing evaluation

2

- **Graphs distance computed using** [Jouili 10]

$$\gamma(n_i) = \left\{ \alpha_i,\ \theta(n_i),\ \{\theta(n_j)\}_{\forall ij \in E},\ \{\beta_{ij}\}_{\forall ij \in E} \right\}$$

- **k-Nearest Neighbor [Cover67]:** to search for similar images (k=1 / k=3 / k=5)

- **Majority voting process**: for k=3 and k=5

Shapes

k	Recognition rate
1	73.7 %
3	92.5 %
5	95.8 %

Textures

k	Recognition rate
1	60.6 %
3	62.8 %
5	62.8 %

Statistical
Image processing evaluation

3

- **Similarity measures**

$$Sim_{i_1,i_2} = (1-(R_L * R_S)) * D_{Patt}$$

$$\sqrt{\sum_{i=1}^{n} |x_i - y_i|^2}$$

- **k-Nearest Neighbour [Cover67]:** to search for similar images

- **Majority voting process**: for k=3 and k=5, to find the most frequent style among outputs

Shapes

k	Recognition rate
1	63.4 %
3	64.6 %
5	70.1 %

Textures

k	Recognition rate
1	78.8 %
3	78.2 %
5	78.5 %

Fusion / layer

Complexification

4

- Shape's descriptions fusion

k	Statistical	Structural	Total
1	63.4 %	73.7 %	90.8 %
3	64.6 %	92.5 %	96.4 %
5	70.1 %	95.8 %	98 %

- Stroke's descriptions fusion

k	Statistical	Structural	Total
1	78.8 %	60.6 %	85.2 %
3	78.2 %	62.8 %	86.3 %
5	78.5 %	62.8 %	87.4 %

Global fusion

Complexification

5

Recognition rates using a majority voting process on all the features available

Layer	Shapes		Textures		
k	Statistical	Structural	Statistical	Structural	Total
1	63,1 %	73,7 %	78,8 %	60,6 %	96,9 %
3	67 %	92,5 %	78,2 %	62,8 %	98 %
5	70,1 %	95,8 %	78,5 %	62,8 %	98,6 %

Discussions on image description

- Framework for historical images analysis
  - Decomposes images in layers
  - Describes each layer using complex description
    - Statistical signature
    - Structural signature
  - Makes the fusion between different kind of description

- Advantage
  - Mix of signatures provides good results

- Drawbacks
  - Far away from historian's keywords

- Need to take into account historian's knowledge
  - To formally represent them
  - To combine them with image processing results

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II. Knowledge management
- To represent historian's knowledge
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Knowledge management

- Need to model and to structure:
  - Knowledge from historians
  - Knowledge from algorithms

- Need to be able to deal with:
  - Low level semantic knowledge
  - High level semantic knowledge

- Need to propose a framework to reduce semantic gap

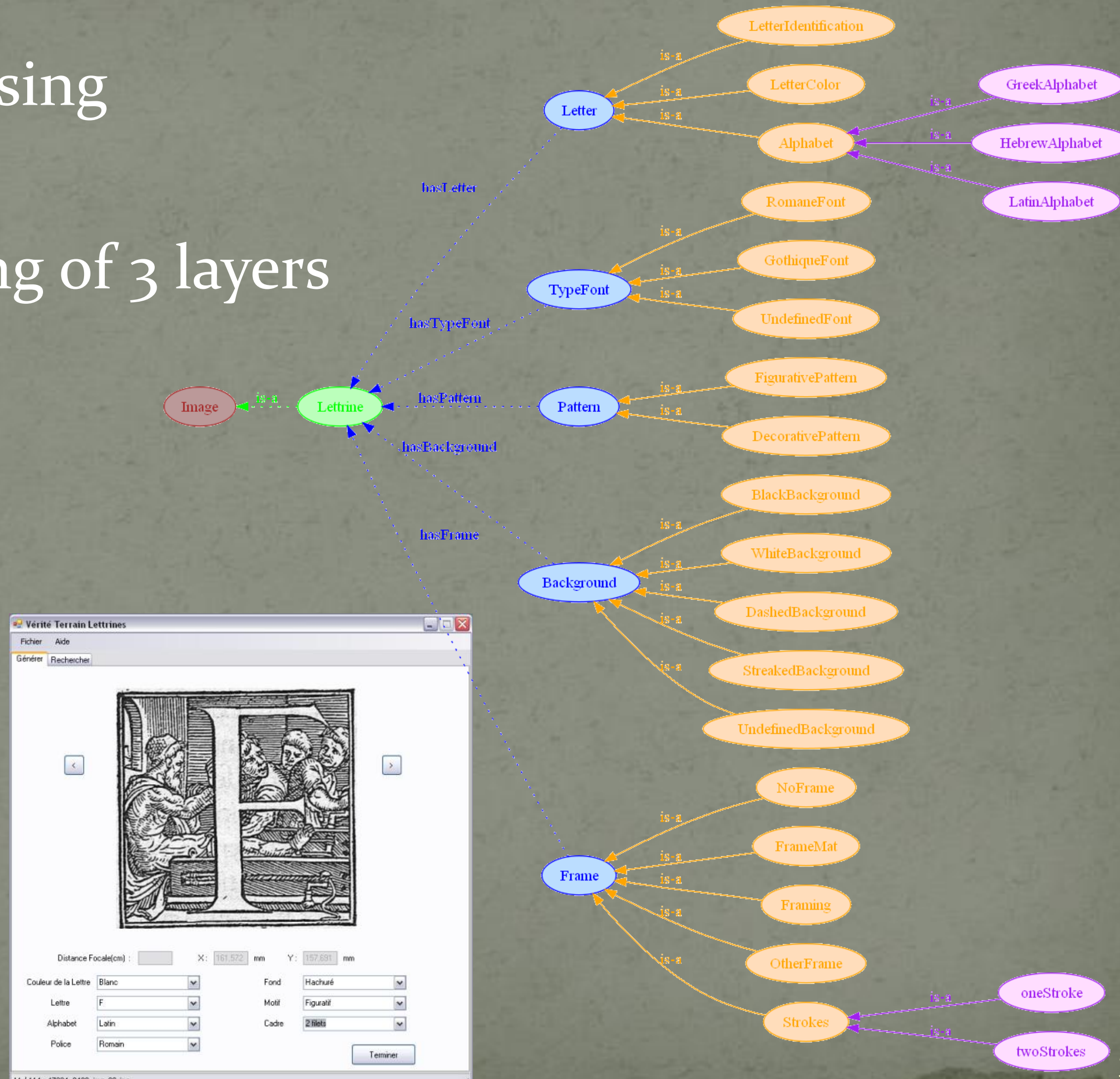
Ontologies

Outlines of knowledge management

- Ontology of historian's knowledge
- Ontology of image processing's knowledge
- Final ontology
- Ontologies evaluation

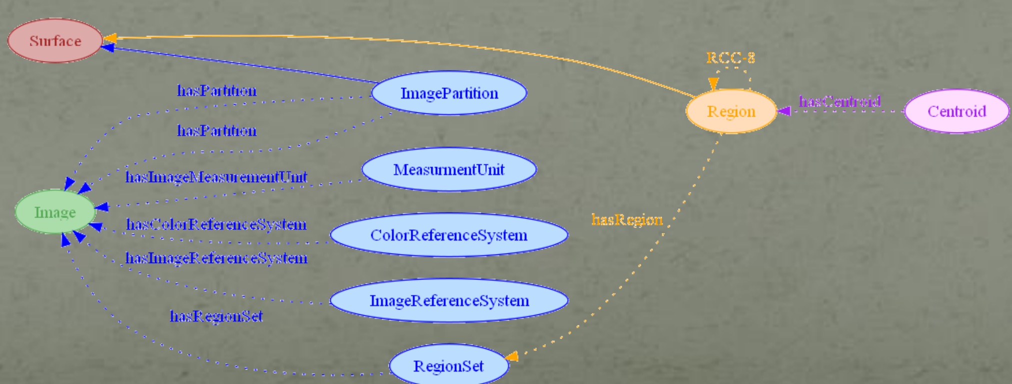
Knowledge issuing from historians

- Obtained by discussing
- Lettrine: overlapping of 3 layers
  - Background
  - Pattern
  - Letter
    - Identification
    - Alphabet
    - Colour
    - Font
- Surrounder by a frame



Knowledge issuing from image processing

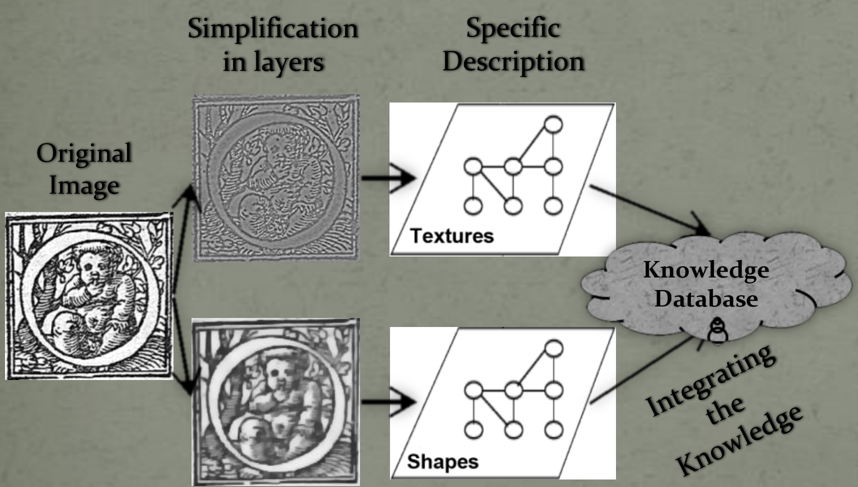
- Lettrines
  - Complex images
  - Composed of semantic elements
- Ontology
  - Represent an image as a set of regions
    - Regions are issuing from our algorithms
  - Represent the description of each region

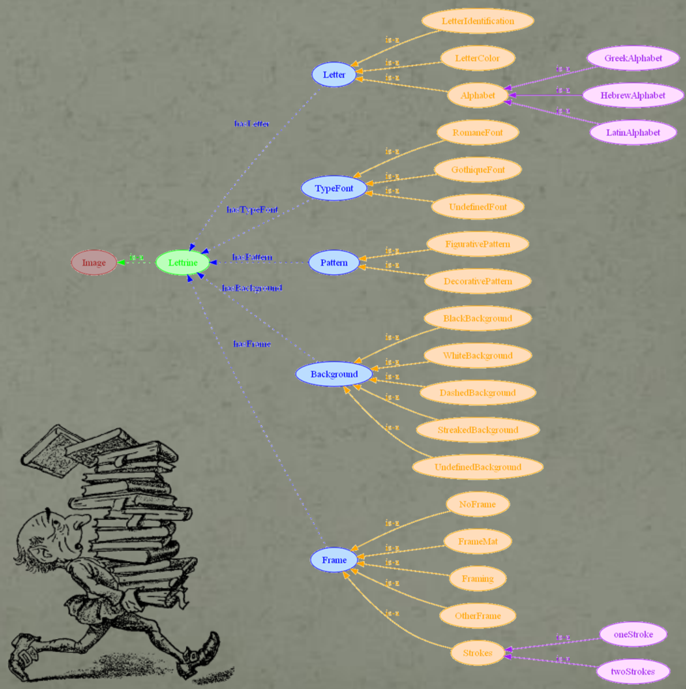


Summary

QbE / CBIR

Keywords from experts

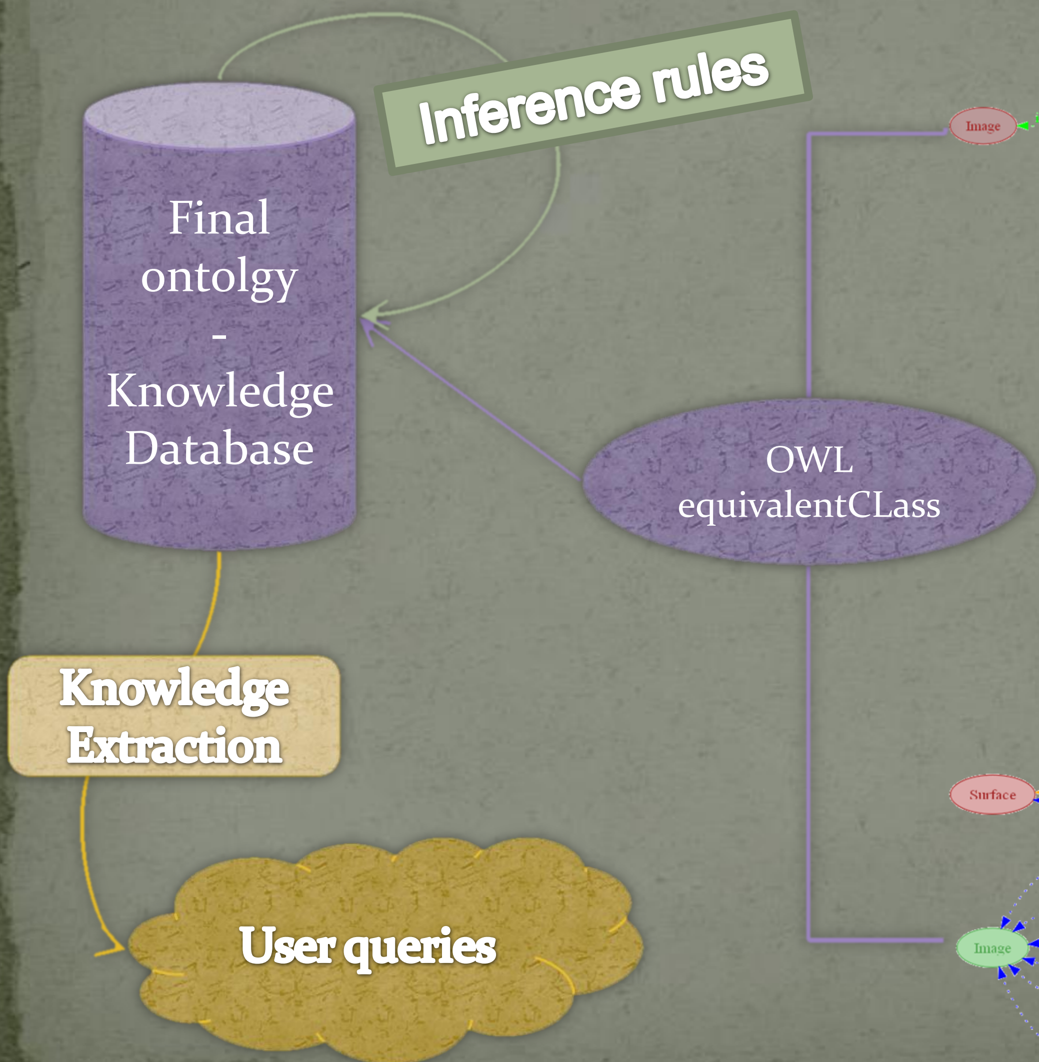


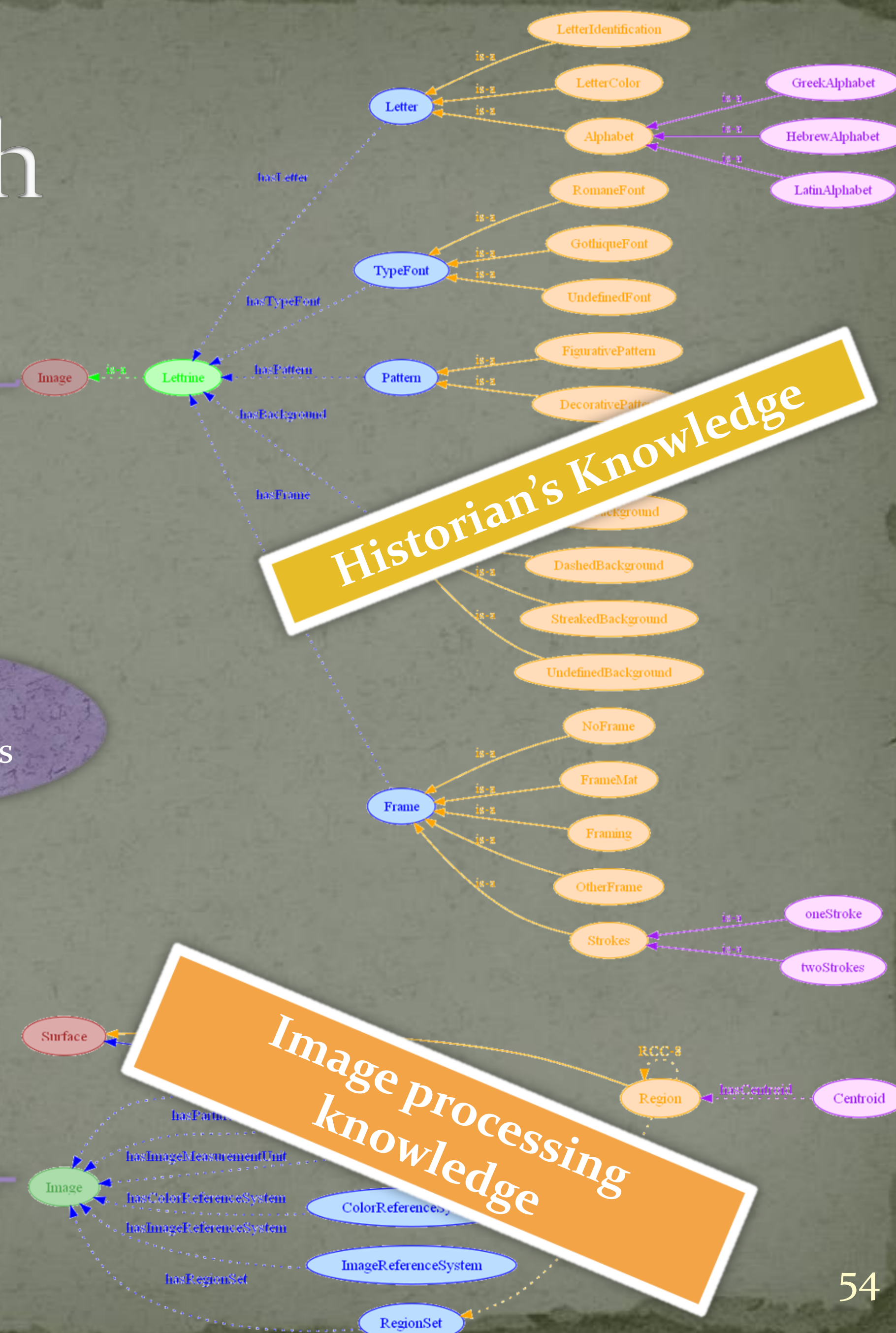


Outlines of knowledge management

- Ontology of historian's knowledge
- Ontology of image processing's knowledge
- Final ontology
  - Link between two precedent ones
  - Enriched with inferences rules
- Ontologies evaluation

Proposed approach





Inference Rules

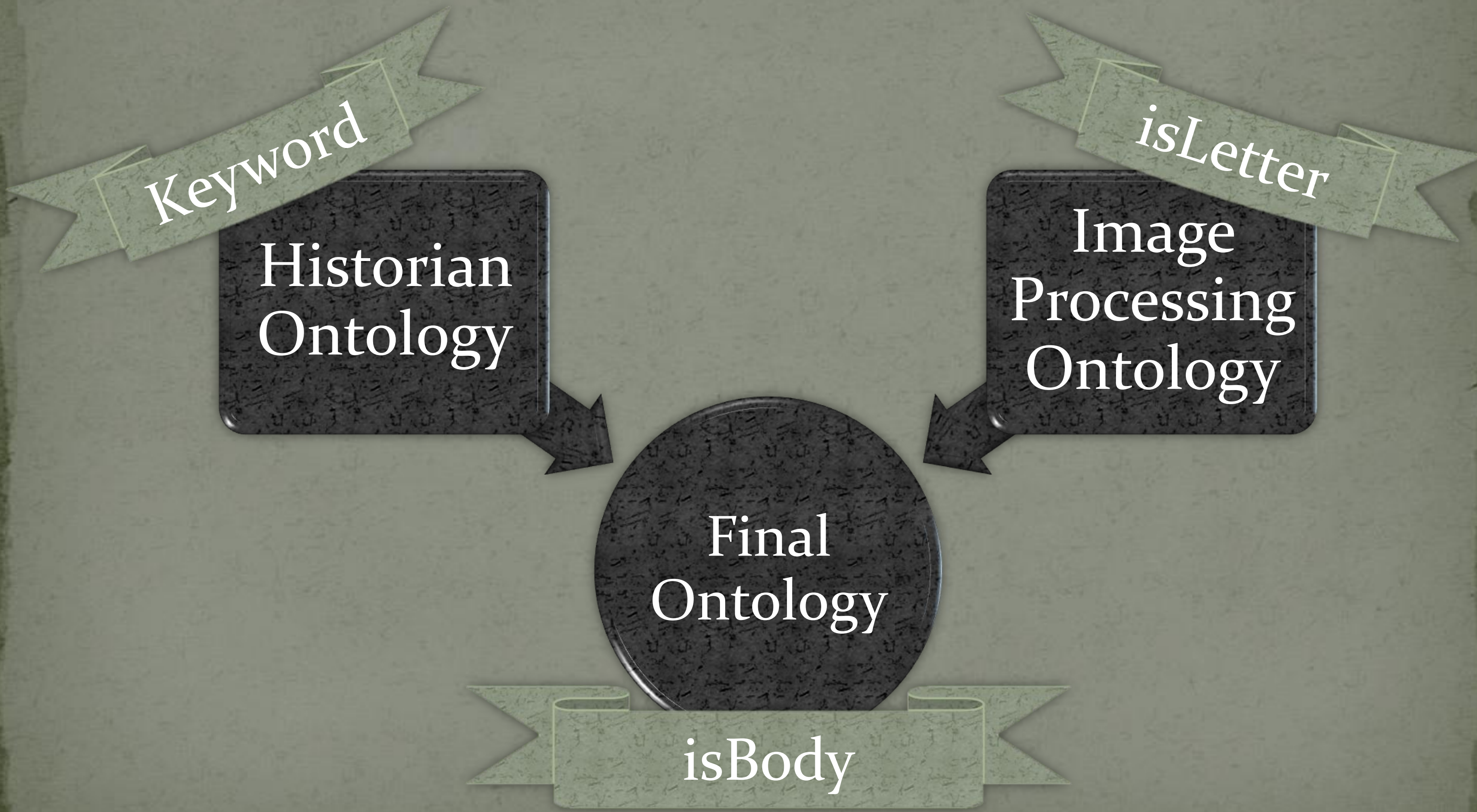
- Allow reasoning on knowledge database
- Enrich the knowledge database
  - By using values from different concepts
  - By adding implicit knowledge
- Applied on extracted regions and historian's annotations
- New knowledge: addition of new properties

New properties

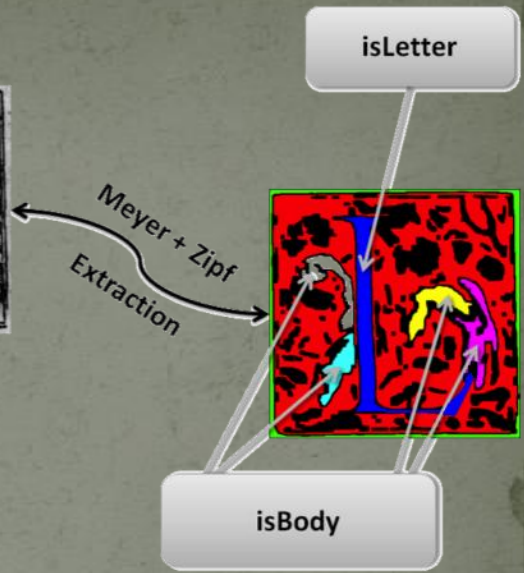
=

link between keywords and low level features

Semantic gap reduction: evaluation



Inference rules



isLetter

- Located in the center of the image
- With few holes
- The biggest region that satisfies the two first criteria

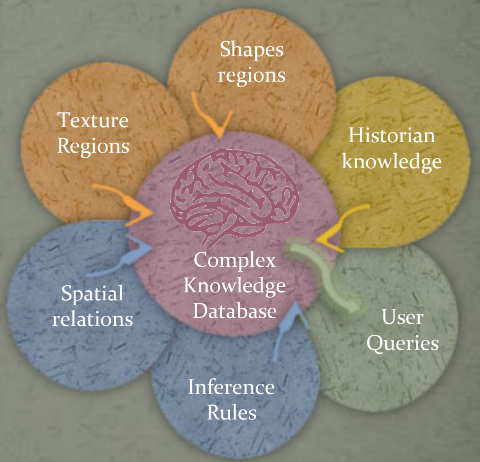
Computer science knowledge

Historian knowledge

Deduced knowledge

- Lettrine has a figurative pattern
- The region has few holes
- The region is light grey
- The region is in the center of the lettrine
- The region is not labelled as « isLetter »

isBody



Inference rules evaluation

	isLetter	**isBody**
Number of images	100	45
Number of candidate regions	584	112
Detection rate	91%	98%

Discussions on knowledge management

- Global system to manage knowledge
  - Issuing from historians
  - Issuing from image processing
  - Based on ontologies

- The system propose a solution to reduce the semantic gap
  - Using inference rules

- We propose a system that enables
  - Query by example
  - Query using keywords from the expert domains

Conclusion

- Global framework to analyse complex images
- Creates a link between two domains
- Allows reducing semantic gap using inference rules
- Allows query by example and keywords query
- Tested on old document images (lettrines)

Perspectives

- Image description
  - Use of another image simplification
    - Allows more layers
    - Could be extended to natural images
  - Propose an early fusion of signatures
    - To compare with late fusion

Perspectives (2)

- Ontologies
  - Extend our model to others expert domain
    - Some works on comics are actually starting in L 3i
- Inference rules
  - Propose rules on texture layer
    - To retrieve hashed background
    - To combine with rules on shapes
  - Propose automatic extraction of rules
    - Using relevance feedback
    - Using Machine learning algorithms

Publications related to this work

- 20 Publications into journals and conferences
  - 2 international journal papers (IEEE-SMCB / IJDAR)
  - 1 national journal paper (TSI)
  - 3 springer book sections (2 LNCS – 1 SCI)
  - 1 invited conference (EUSIPCO 2011)
  - 13 international and national conferences

*We wish to thanks the CESR for the lettrines

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