Soutenance de Master Recherche Mathématiques et Applications

Spécialité : Systèmes Dynamiques et Signaux

Image interpretation and conceptual graph integrating topologic and photometric knowledge

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LABORATOIRE D'INGÉNIERIE DES SYSTÈMES AUTOMATISÉS

7 July 2011

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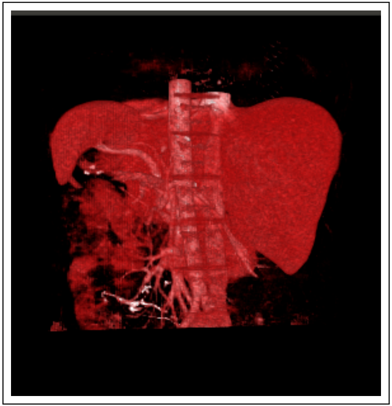
EA 4094 - Université d'Angers

Plan

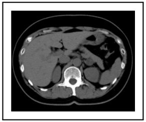
1. Introduction
2. Knowledge representation
3. Inference engine
4. Evaluation
5. Application
6. Conclusion



Road map

1. Introduction
   - Presentation
   - Image content understanding
   - Problem statement
   - State of the art
   - Steps
2. Knowledge representation
3. Inference engine
4. Evaluation
5. Application
6. Conclusion

Presentation



1. Internship from March to July 2011
2. Image analysis for diagnostic assistance
3. Previous work : state of the art
4. Programming language : Python 2.7

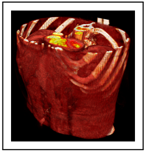
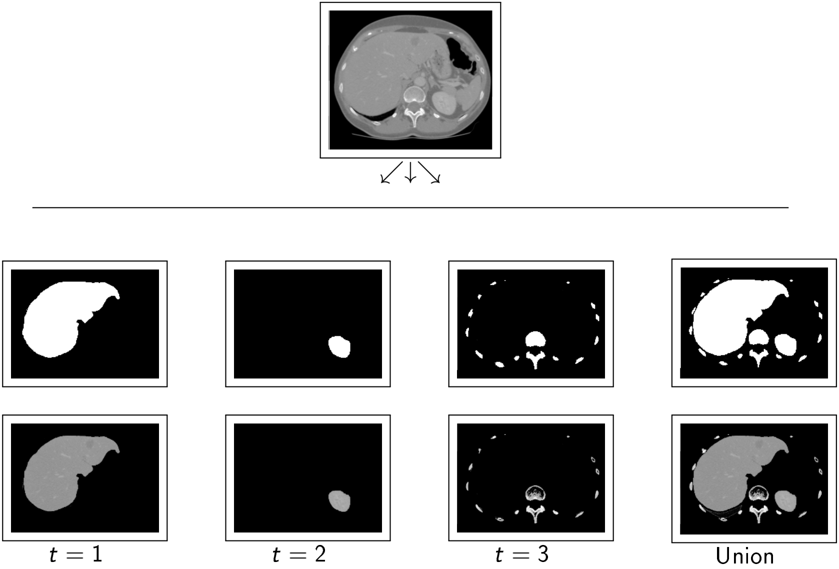


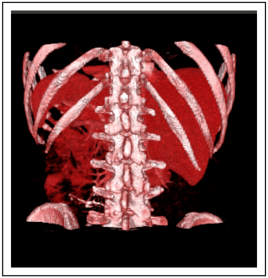
Image content understanding : sequential approach



Problem statement

How to represent and use non quantitative informations for image content understanding ?

1. e.g. vessels are not included in bones $\Rightarrow$ topology
2. e.g. vessels are more bright than liver $\Rightarrow$ photometry



$\Rightarrow$

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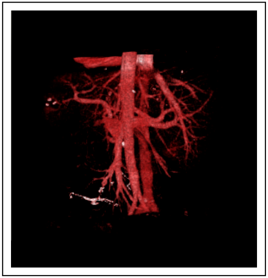


What about state of the art ?

Image interpretation with a priori conceptual knowledges

Example : topological (e.g A include B), relative distance (e.g. A close to B), relative position (e.g. A is left to B)

1. Not common in image interpretation
2. Nature
   - Quantitative (e.g. distance, intensity) [1]
   - Non quantitative (e.g. inclusion, intersection) [2]
3. Representation as graph [3]
   - Contextual addition : active node [2]

Contribution

Sequential approach with topological and photometrical knowledges.

1. [3] C. Hudelot, J. Atif, and I. Bloch, Fuzzy spatial relation ontology for image interpretation, *Fuzzy Sets and Systems*, 2008
2. [2] J.-B. Fasquel, V. Agnus, An interactive medical image segmentation system based on the optimal management of regions of interest, *Computer Methods and Programs in Biomedicine*, 2006
3. [1] A. Deruyver, Y. Hodéb, and L. Brun, Image interpretation with a conceptual graph, *Artificial Intelligence*, 2009

Steps

Representation

1. Knowledge (conceptual information)
2. Segmentation process (contextual information)

Formalization (inference engine)

1. Region of interest (topology)
2. Number of classes (photometry)
3. Class ordering (photometry)

Evaluation

1. Synthetic images
2. Clustering algorithm
3. Method's benefits quantification

Application

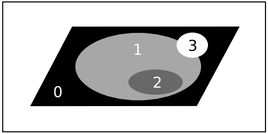
1. Medical images
2. Cluster identification
3. Windowing for volume rendering

Road map

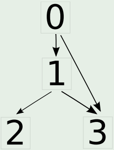
Topology & photometry (conceptual informations)

Graph

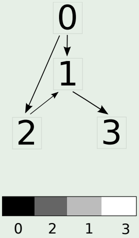
1. Nodes are regions (e.g 0, 1, A, B, liver, tumor)
2. Edges are relations (e.g. include, less bright than)



Topology



Photometry

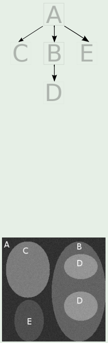


Segmentation process modeling (contextual informations)

Add contextual information to the previous graph

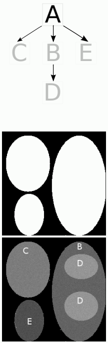
1. Active node = type is segmented
2. Non active node = type is not segmented

Date $t = 0$



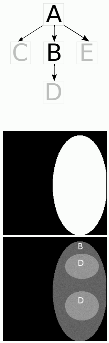
A $\Rightarrow$

Date $t = 1$



B $\Rightarrow$

Date $t = 2$



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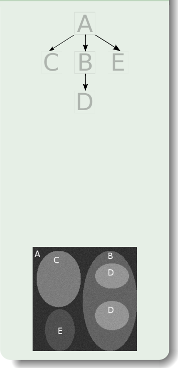

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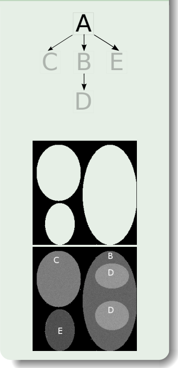

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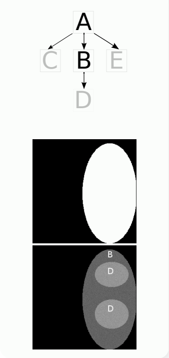

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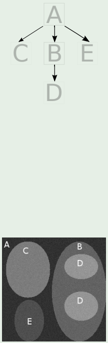

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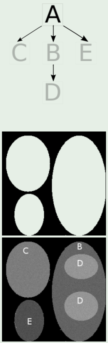

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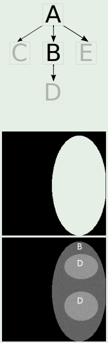


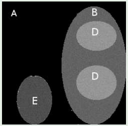
Road map

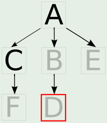
From the optimal region of interest...

Optimal Region Of Interest [1]

$$R_t(u) = \left(\bigcup_{\bar{l} \in G^{-1}_{T,t}(u)} X_t(\bar{l}) \right) \cup \left(\bigcup_{i \in S_t | u \in G^{-\infty}_{T,t}(i)} X_t(i) \right) \quad (1)$$

Example





ROI

$R_t(D) = X_t(\bar{A})$

$R_t(D) = X_t(A) \setminus X_t(C)$

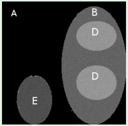
1. [2] J.-B. Fasquel, V. Agnus, *Computer Methods and Programs in Biomedicine*, 2006

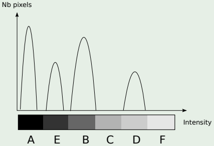
… to the number of classes

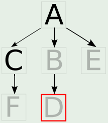
List of classes ⇔ lobes in the histogram

$$L_t(u) = \left\{ i \in (G_T^{\infty}(G_{T,t}^{-1}(u)) \cap (S \setminus S_t)) \mid (G_{T,t}^{-1}(i) \cap G_{T,t}^{-1}(u) \neq \emptyset) \right\} \cup G_{T,t}^{-1}(u) \quad (2)$$

Example







Cardinality

A priori number of classes in the ROI :
$N_t(u) = |L_t(u)|$
$N_t(D) = |L_t(D)| = |B, E, D, A|$
$N_t(D) = 4$

Identification

Ordering by photometry :
$O_t(u) = \text{ord}\{L_t(u)\}$
$O_t(D) = \text{ord}\{B, E, D, A\}$
$O_t(D) = \{A, E, B, D\}$

Results

Conclusion

1. Not easy as it seems
2. Limit of the study for the number of classes
   - Segmentation of a type in once $\Rightarrow$ no multiplicity
   - Types are all in the image $\Rightarrow$ no optionality

Road map

Presentation

Which evaluation protocol ?

Difficulties

1. Choice of the clustering algorithm
2. Procedure (contextual information)
3. Data (e.g. noise, brightness, region)

Evaluation

1. *K-Means* clustering
2. Synthetic images
3. Benefits of knowledge
   - Reduction of polluting data and volume
   - *K-Means* parameterization

Clustering algorithm

Study limited to only one clustering algorithm to illustrate each benefits.

K-Means

1. A widely used clustering algorithm *"the simplicity and computational speed of the K-means algorithm [...] has made it a popular choice"*[1]
2. Initialization parameters (k, centroid) *"the algorithm needs initializing values which greatly influence its terminating optimal solution ... good initialization is crucial for finding globally optimal partitionings"*[1]

1. [4] Anna D. Peterson Ranjan Maitra and Arka P. Ghosh. , A systematic evaluation of different methods for initializing the k-means clustering algorithm, *Computer Methods and Programs in Biomedicine*, 2010

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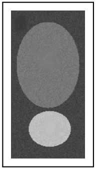

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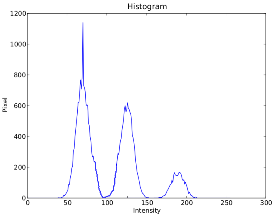

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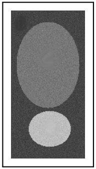
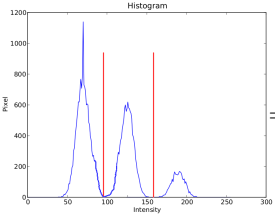


$\Rightarrow$



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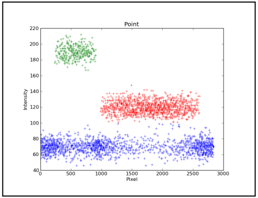

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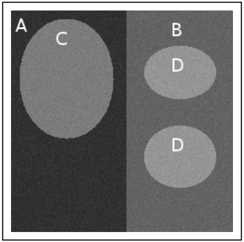
ROI + number of classes ⇒ reduction of polluting data and volume



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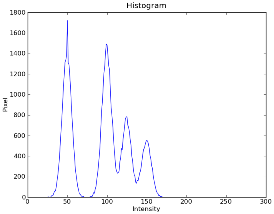
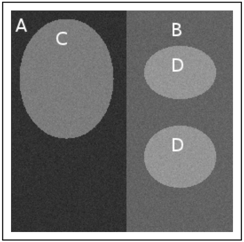


4 classes

ROI + number of classes ⇒ reduction of polluting data and volume



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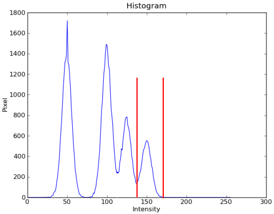
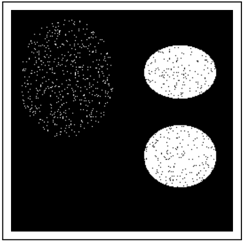


D
⇒



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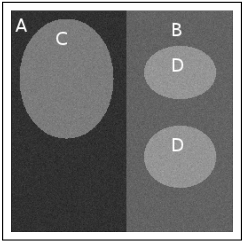

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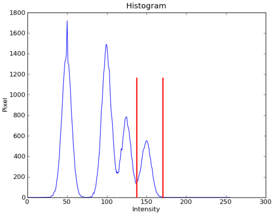
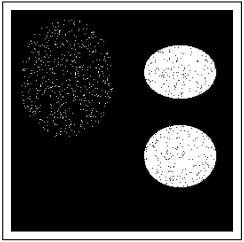
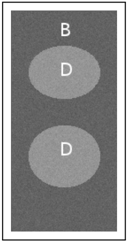


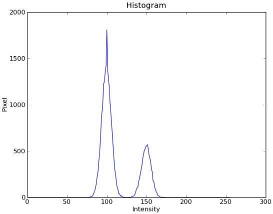
D ⇒



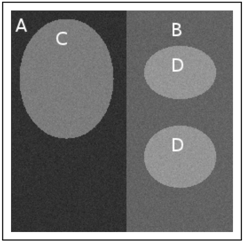


2 classes

⇒



ROI + number of classes ⇒ reduction of polluting data and volume



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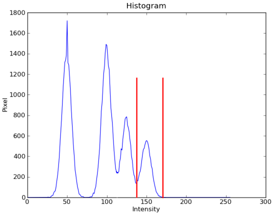
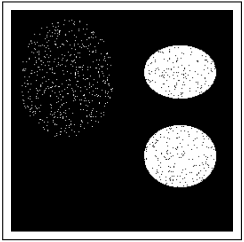


D ⇒



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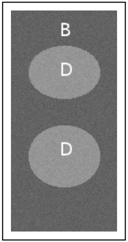

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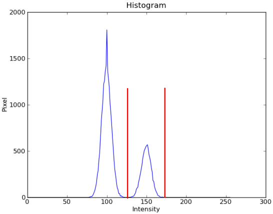

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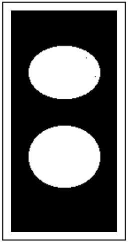
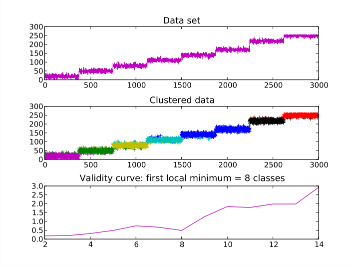
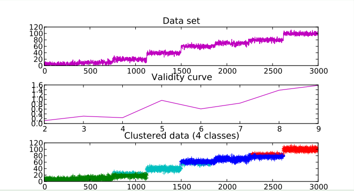


ROI improve efficiency and save time.

Number of classes ⇒ K-Means parameterization

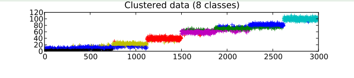
No a priori number of clusters [1]





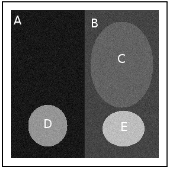
A priori number of cluster

1. Computing time saving
2. Optimal clustering

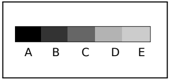


1. **[5, Ray - 1999] S Ray and R H Turi, Determination of number of clusters in k-means clustering ..., *Advances in Pattern Recognition and Digital Techniques*, 2007**

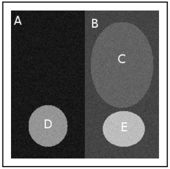
Number of classes + ordering = centroids ⇒ K-Means parameterization



5 classes



Number of classes + ordering = centroids ⇒ K-Means parameterization



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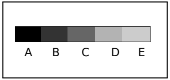
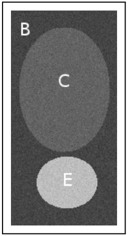
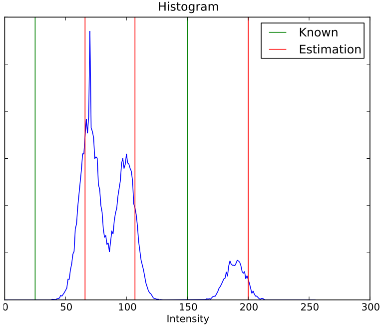
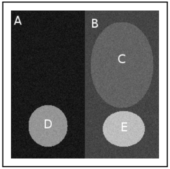




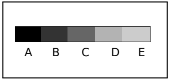
3 classes

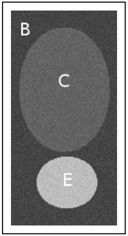


Number of classes + ordering = centroids ⇒ K-Means parameterization

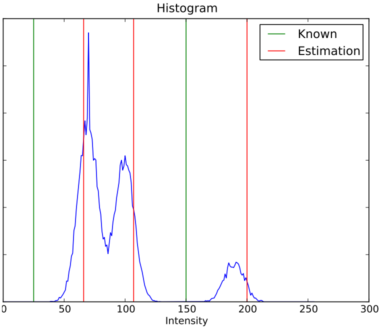


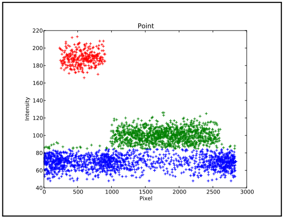
5 classes

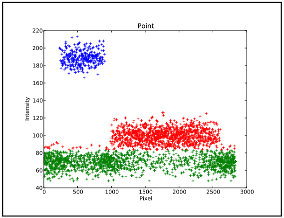


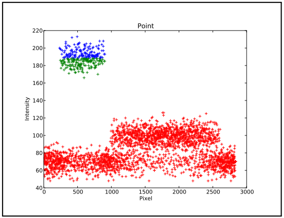


3 classes







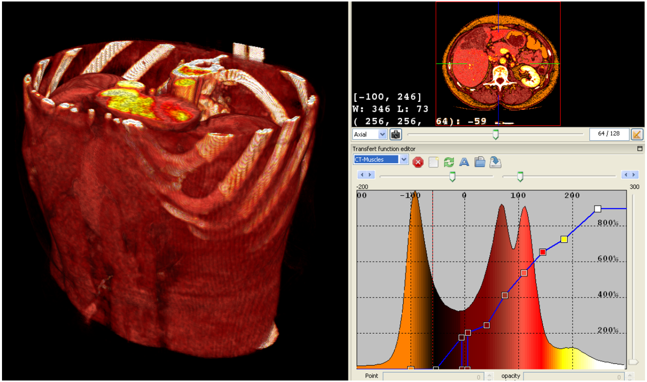


Careful seeding = better clustering

Road map

Presentation

1. Visualization only : less restrictive than segmentation
2. Preliminary results for two use cases
3. Medical image from IRCAD [1] database (ground truth)



1. IRCAD : Institut de Recherche contre les Cancers de l'Appareil Digestif

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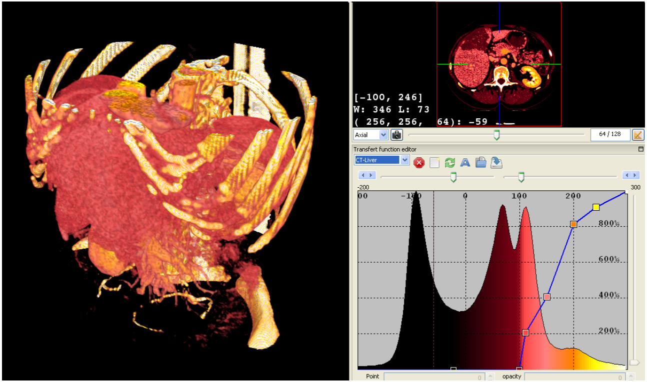
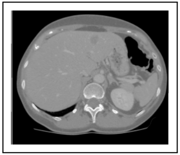
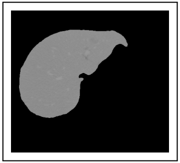


1. IRCAD : Institut de Recherche contre les Cancers de l'Appareil Digestif

Context



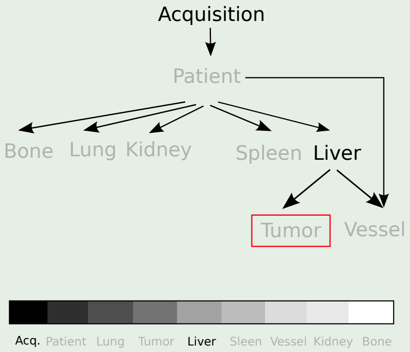
$t = 0$



$t = 1$

$\Rightarrow$

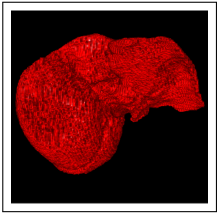
A priori knowledges

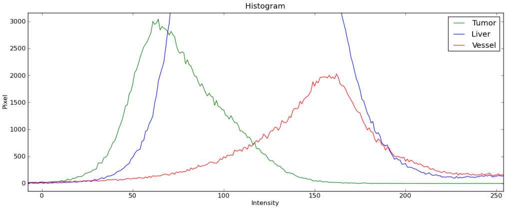


Inference engine

1. Number of classes = 3
2. Ordering = tumor < liver < vessel

Clustering and windowing for tumor





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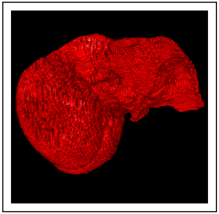
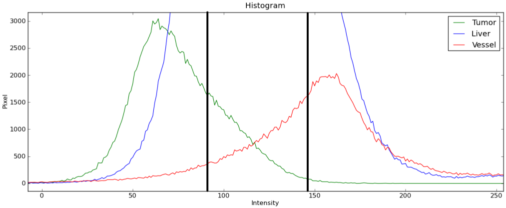
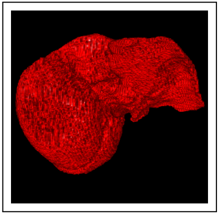
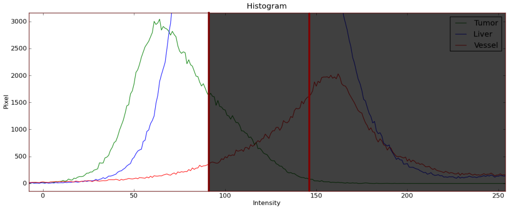


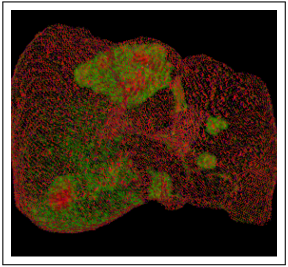


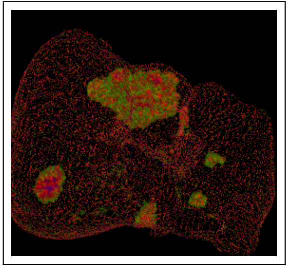
Clustering and windowing for tumor



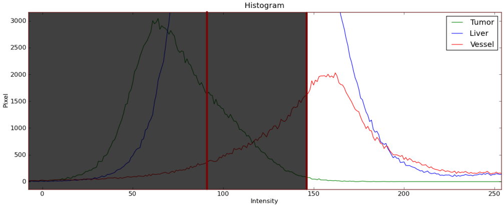


Windowing for tumor

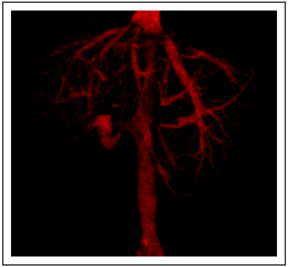


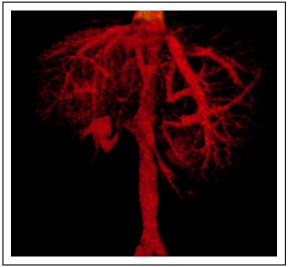


Clustering and windowing for vessel



Windowing for vessel





Road map

Conclusion

Results

1. Generic method for image understanding
2. Non quantitative $\Rightarrow$ adaptability
3. Constraints :
   1. Perfectly segmented masks
   2. Complete graph completion

Refinements

1. N type value to handle multiplicity and optionality
2. Node fully included by successors

Personal

1. Very pleasant job (research, tools)
2. Formalization is not easy
3. The best part just started

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