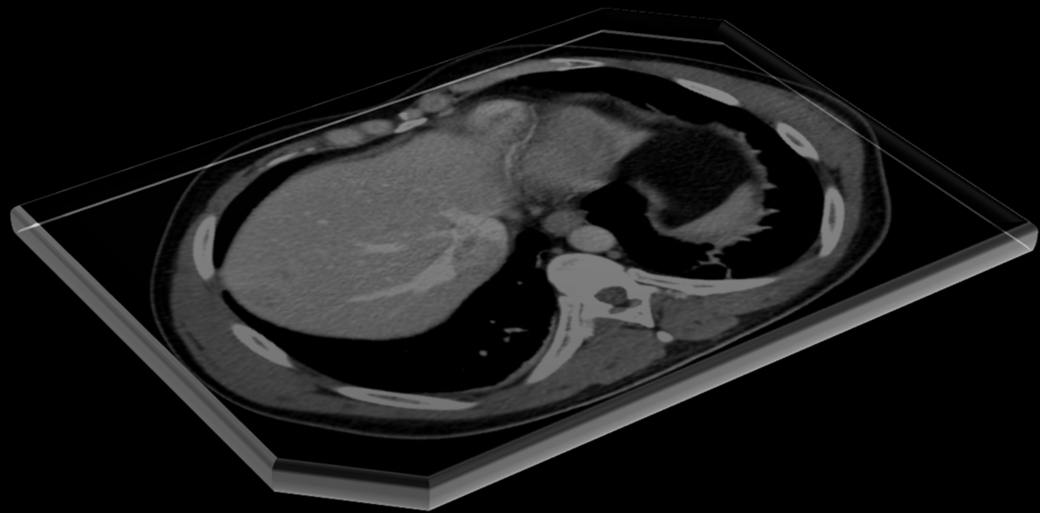
MCBR-CDS (Medical Content-Based Retrieval for Clinical Decision Support), October 1st, 2012

Liver Lesion Classication on Multi-Phase CT



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Laboratoire d'Informatique de Robotique et de Microélectronique de Montpellier

LIRMM

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[3] University Hospital of Montpellier

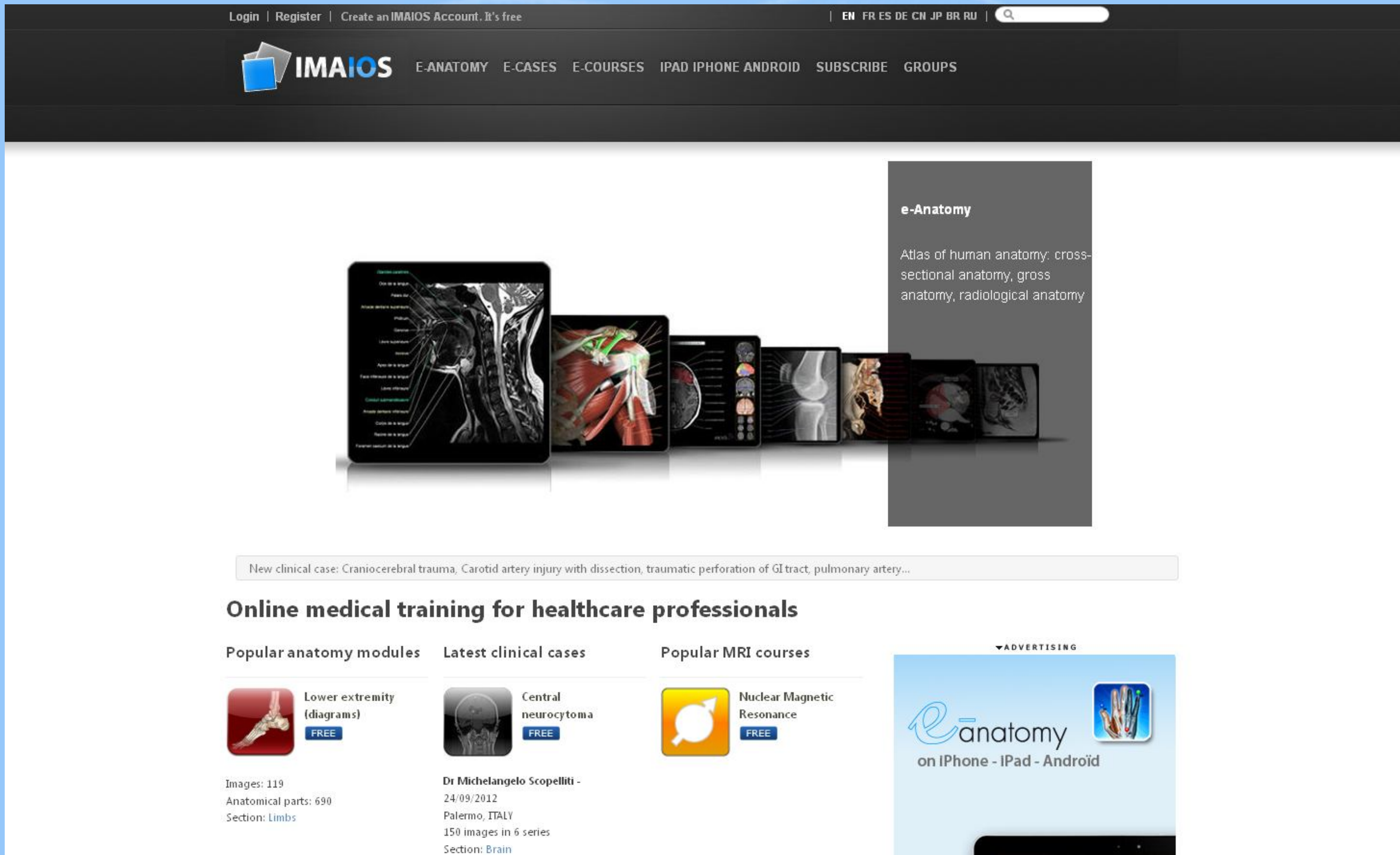
Montpellier, FRANCE

IMAIOS

Layout

- Introduction
- Data
- Method
- Results
- Comparison
- Conclusion

Context



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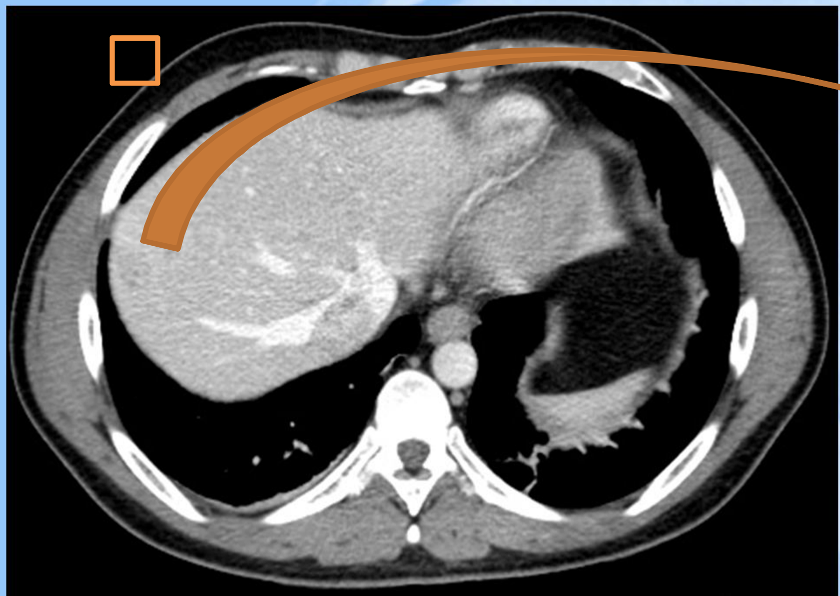
Introduction

Project Overview

Computer Aided Diagnosis (CAD)

Applied on hepatic nodules



Classify this image

Layout

- Introduction
- Data
  - Overview
  - CT scans
  - Region Of Interest
  - Database
- Method
- Results
- Comparison
- Conclusion

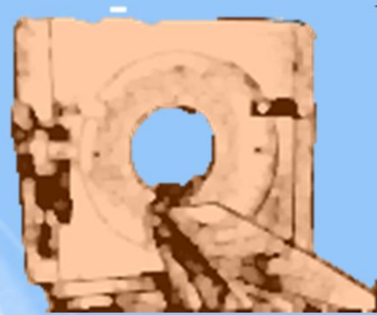
Data

Overview

Retrospective analysis of cases

[2008 – 2011]

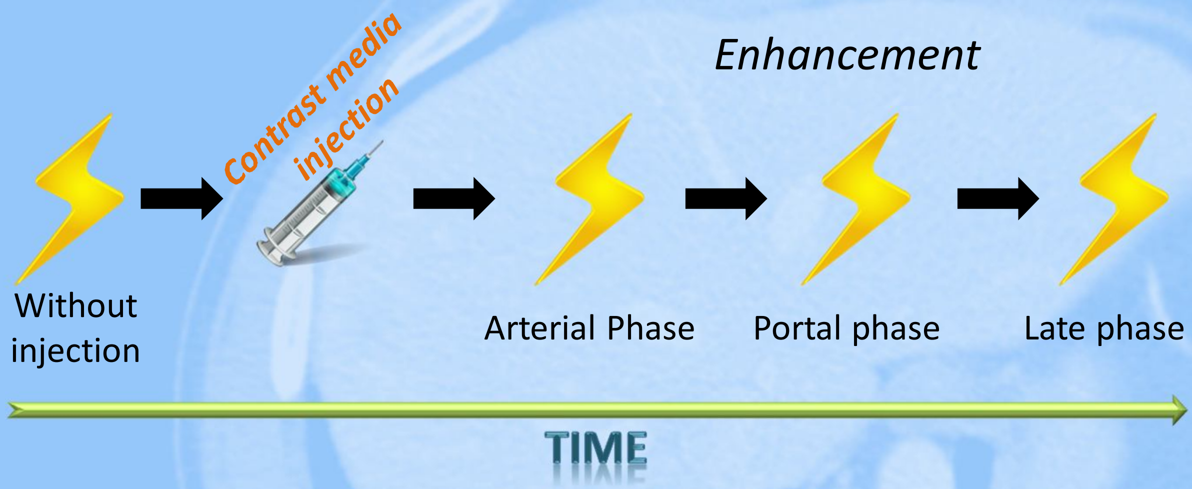
Multi-phase CT scans



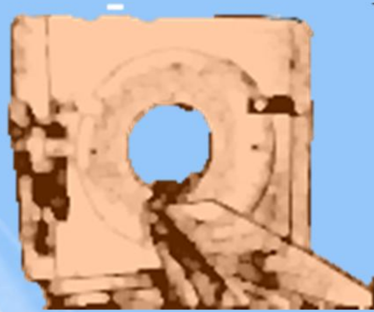
Computer Tomography (CT) multi-phase scans

Multi-phase CT scans

Computer Tomography (CT) multi-phase scans



Multi-phase CT scans



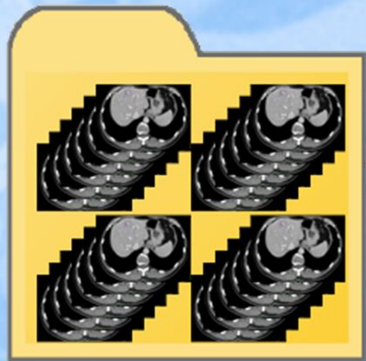
Computer Tomography (CT) multi-phase scans

Contrast media injection

Enhancement

Without injection → Arterial Phase → Portal phase → Late phase

TIME

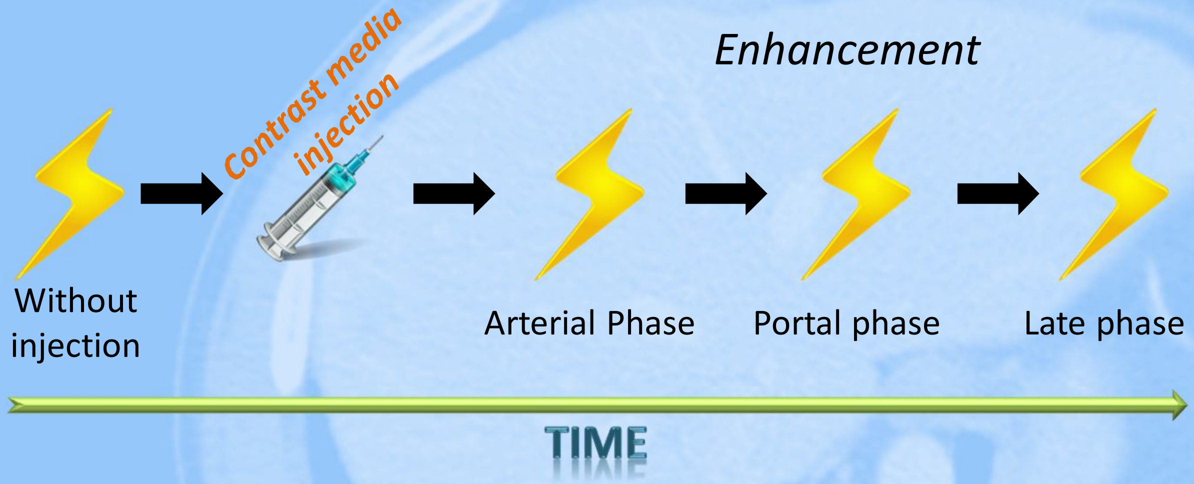


4 series of 2D DICOM *slices*

Data

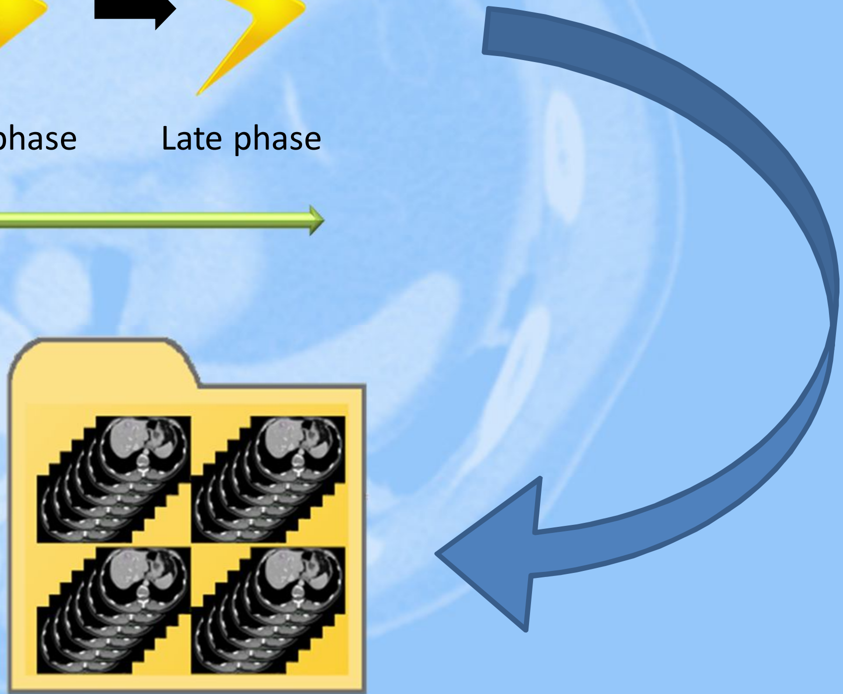
Multi-phase CT scans

Computer Tomography (CT) multi-phase scans



Essential to radiologists to make a diagnosis

But almost absent from CAD hepatic systems

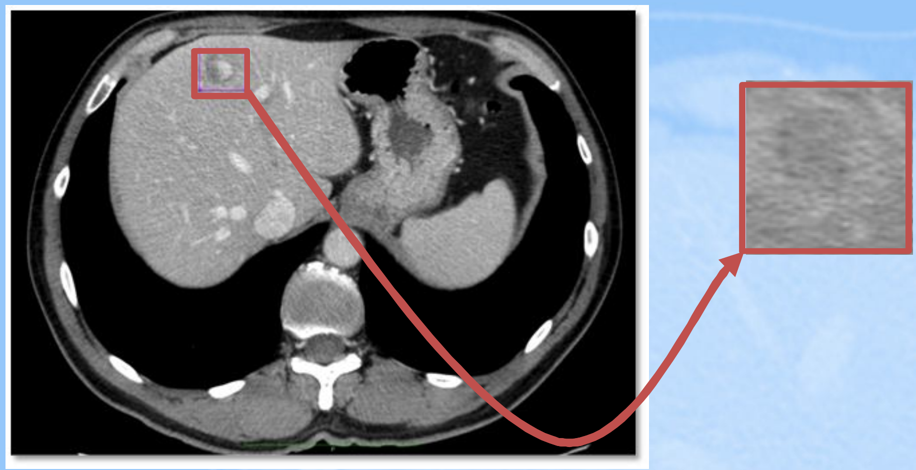


4 series of 2D DICOM slices

Data

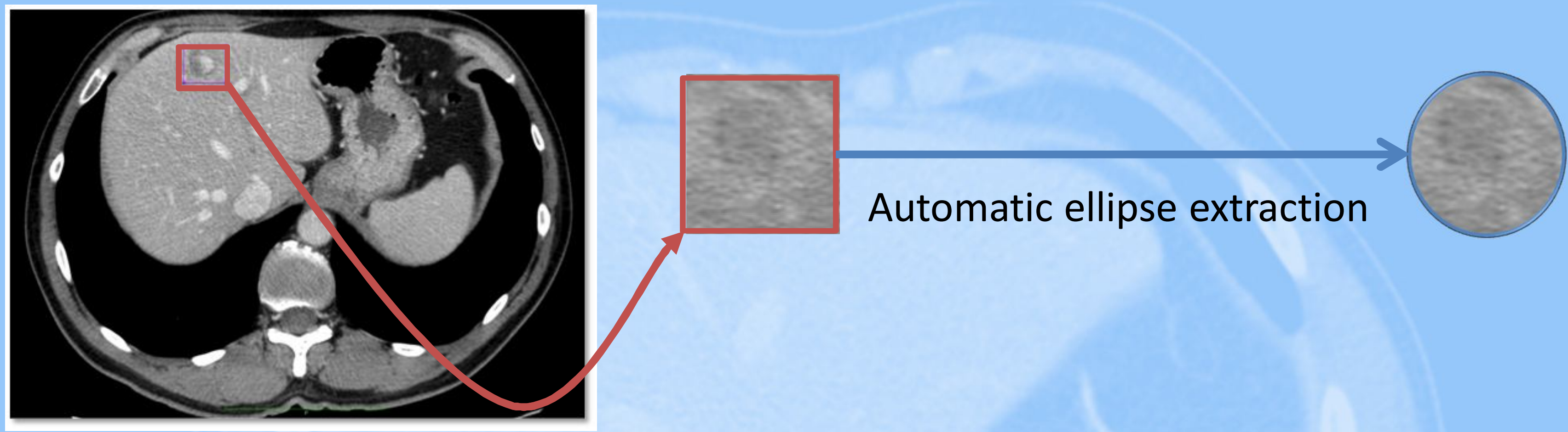
Region Of Interest (ROI)

Region Of Interest (ROI)



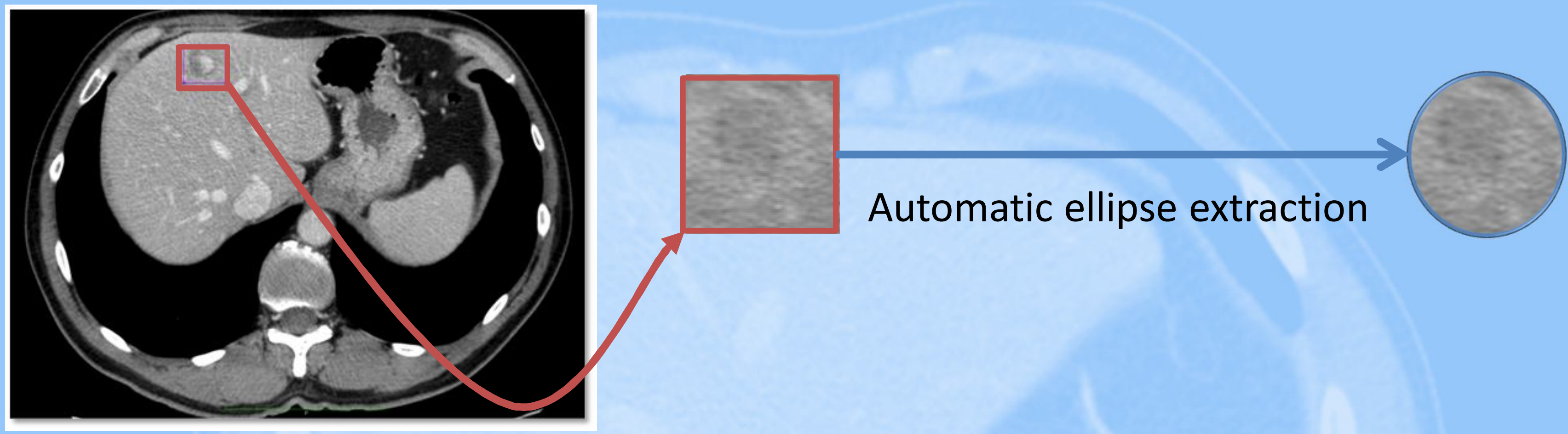
Manual rectangular ROI

Region Of Interest (ROI)



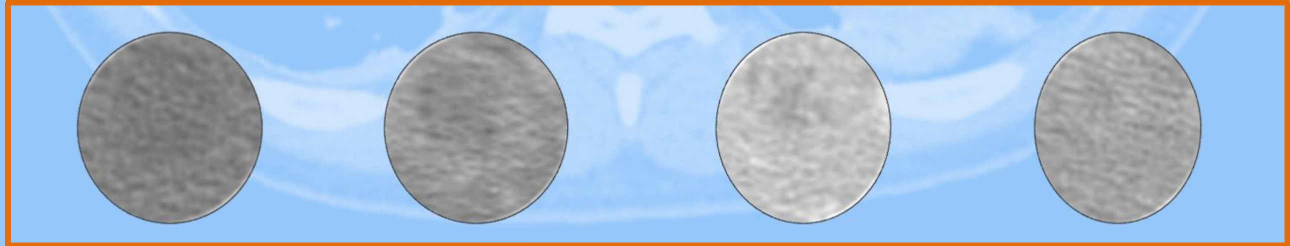
Manual rectangular ROI

Region Of Interest (ROI)



Manual rectangular ROI

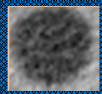
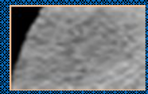
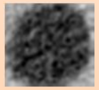
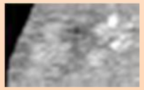
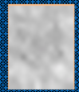
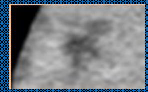
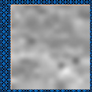
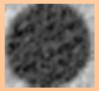
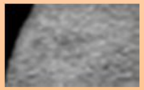
1 lesion ⇔ 4 * 2D ROIs (1 by phase)



Data

Database

95 lesions from 40 patients

Phase / Lesion type	Adenoma	Cyst	Haemangioma	HCC *	Metastasis
1 ***pre-injection***					
2 ***arterial phase***					
3 ***portal phase***					
4 ***late phase***					
Number	**10**	**25**	**9**	**13**	**38**

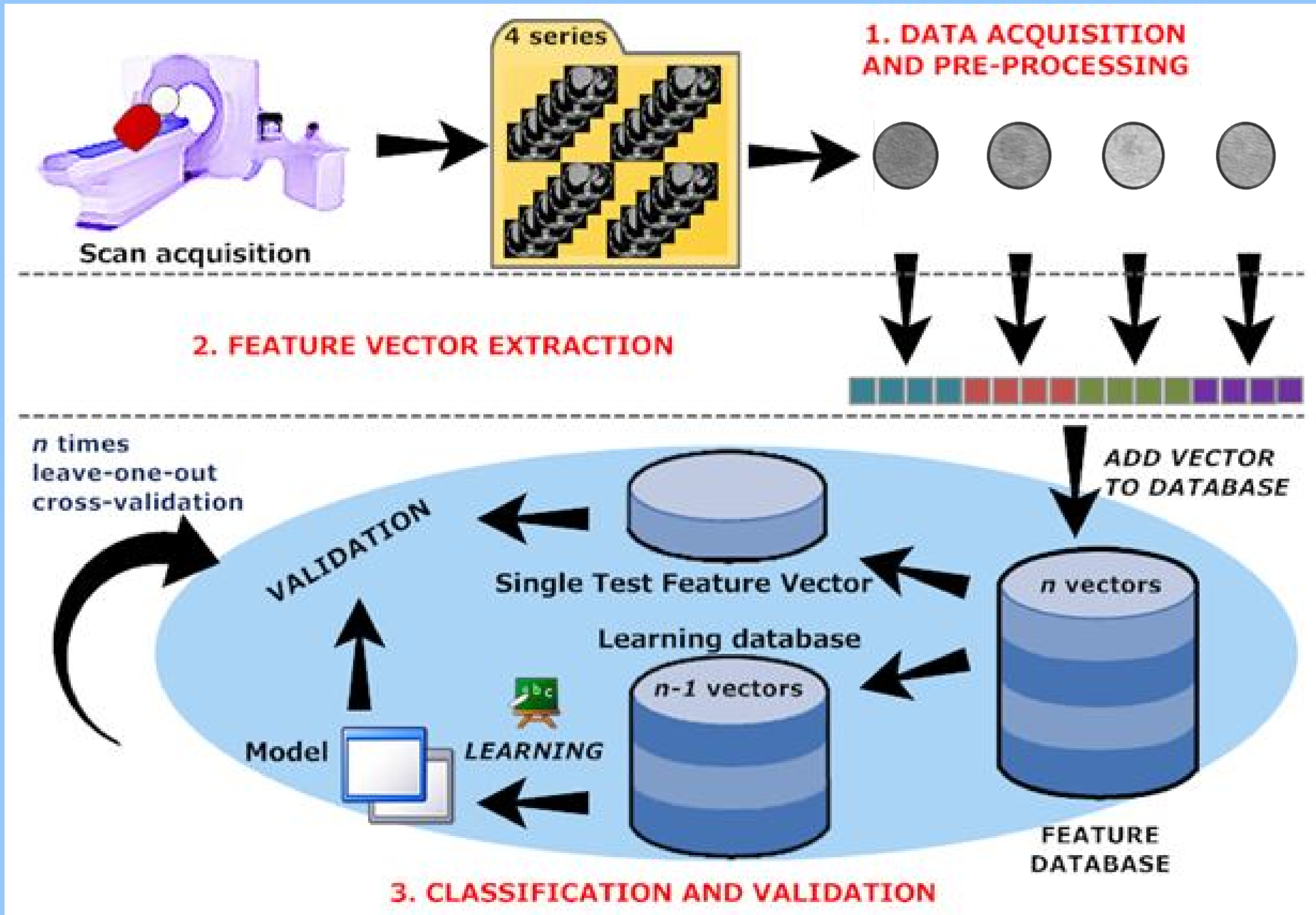
* HepatoCellular Carcinoma

Layout

- Introduction
- Data
- Method
  - Framework
  - Features
  - Classification
  - Evaluation
- Results
- Expert-based analysis
- Conclusion

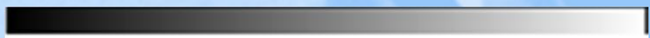
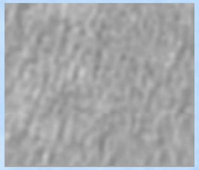
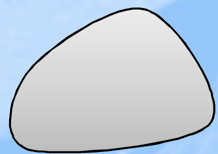
Method

Framework



Features - generalities

They describe:

- the grey levels / color 
- the texture 
- the shape 

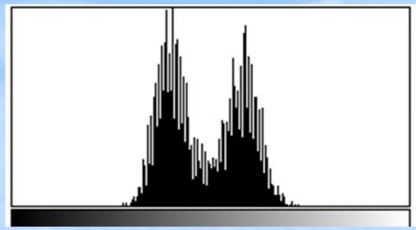
in an image

Method

Feature list

Visual descriptors in our system

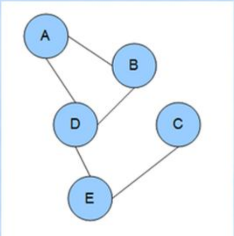
Histogram first order statistics



Statistics computed over the grey-level histogram

ImageJ
Image Processing and Analysis in Java

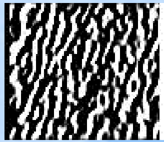
Gaussian Markov Random Fields (GMRF)



[1]Ernst Ising, *Beitrag zur Theorie des Ferromagnetismus*, Zeitschrift für Physik A Hadrons and Nuclei, Springer, issue 1 volume 31 p. 253-258, 1925.

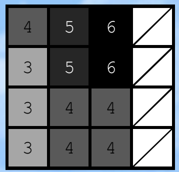
[3] M. Hassner and J. Sklansky, *The use of Markov random fields as models of texture*, Computer Graphics and Image Processing, 12:357–370, 1980.

Law texture measures



K. Laws. Rapid texture identification. In SPIE Vol. 238 Image Processing for Missile Guidance, p.376-380, 1980.

Unser Histogram statistics

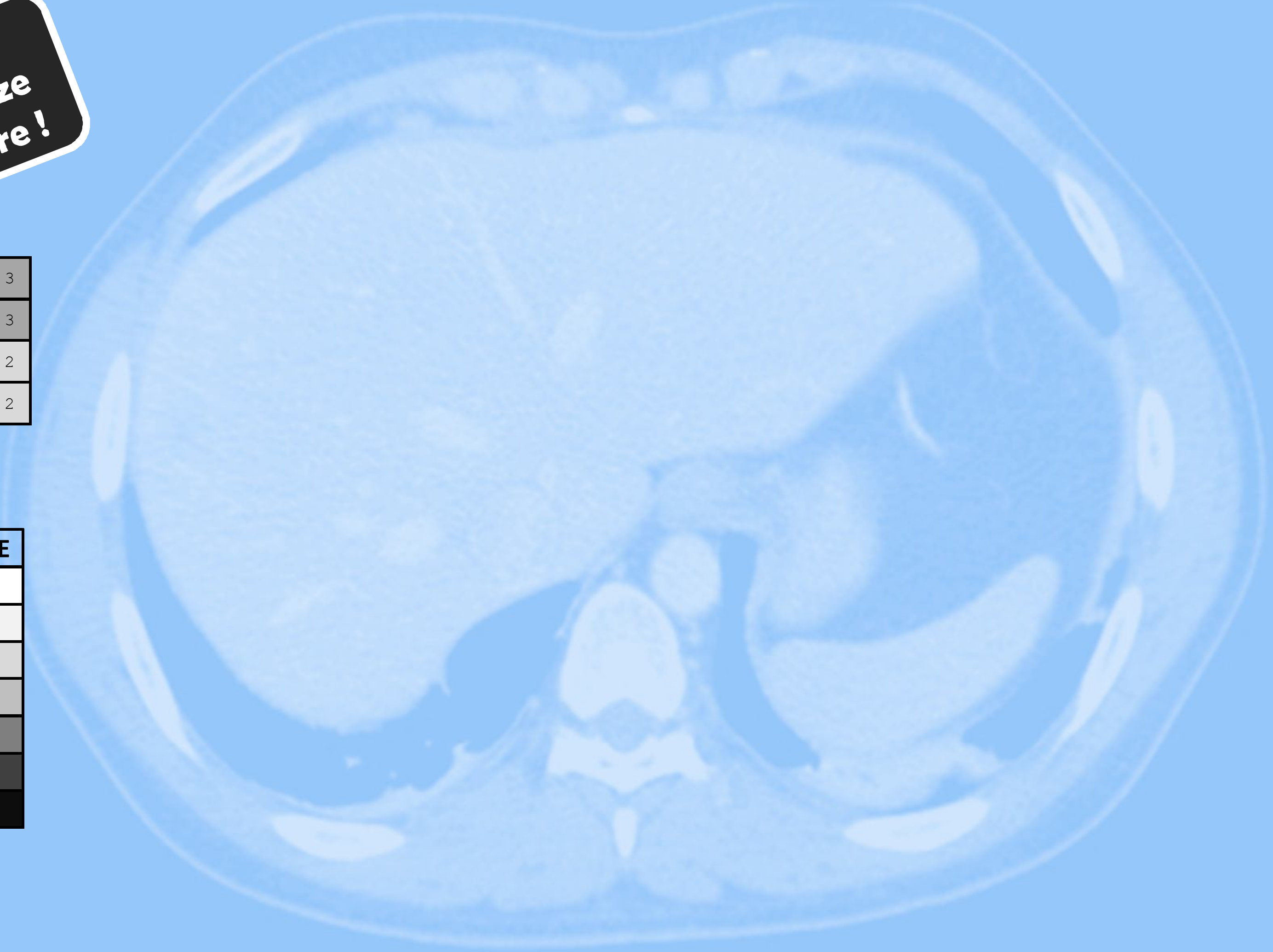


First time applied!

Unser M., Sum and Difference Histograms for Texture Classification, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 8(1), p. 118-125, 1986.

Features: Unser

Let's characterize this texture !



2	2	3	3
1	2	3	3
1	2	2	2
1	2	2	2

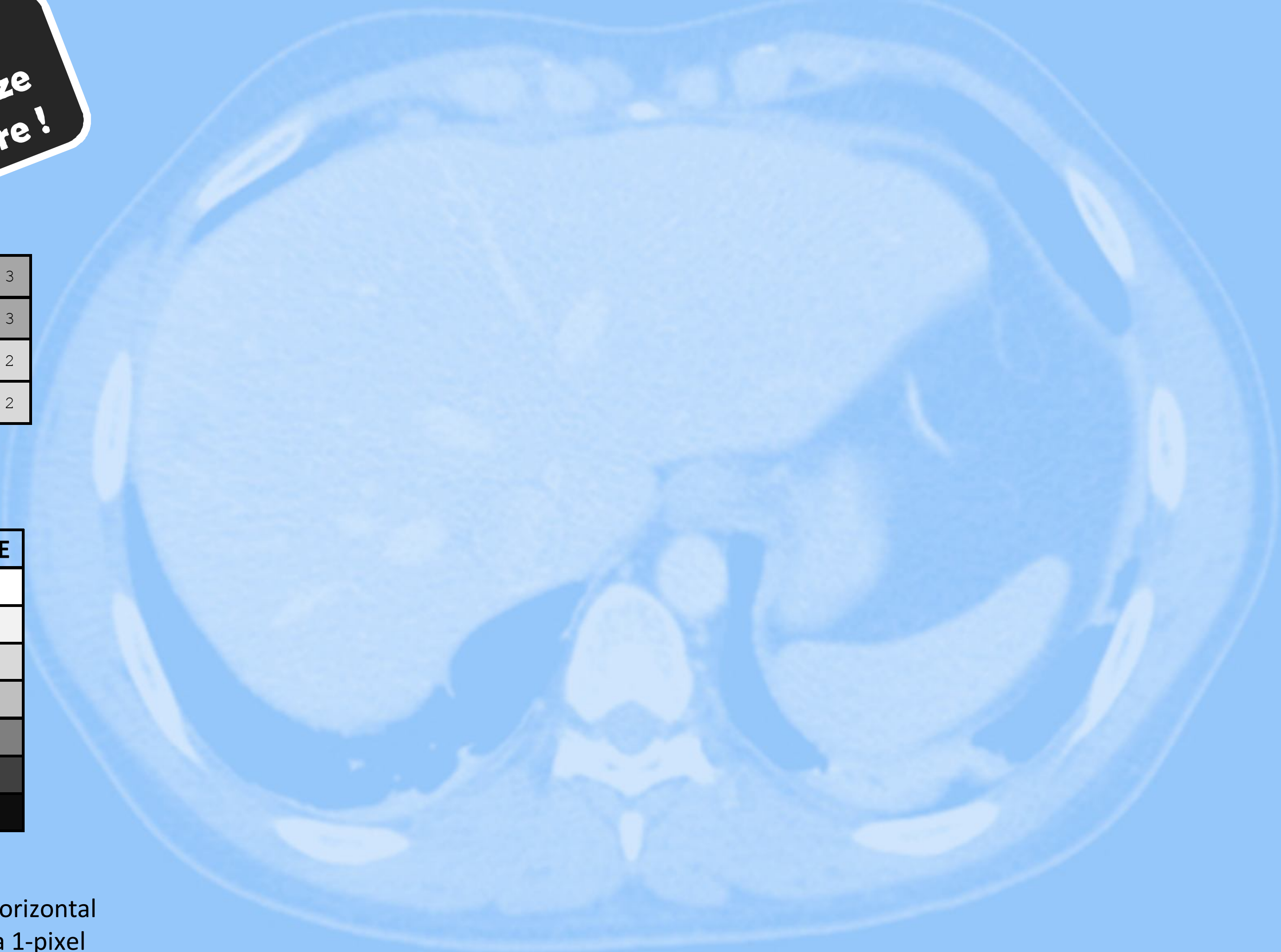
PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	

Features: Unser

Let's characterize this texture !

2	2	3	3
1	**2**	3	3
1	2	2	2
1	2	2	2

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	



Simple example: horizontal orientation from a 1-pixel right distance only

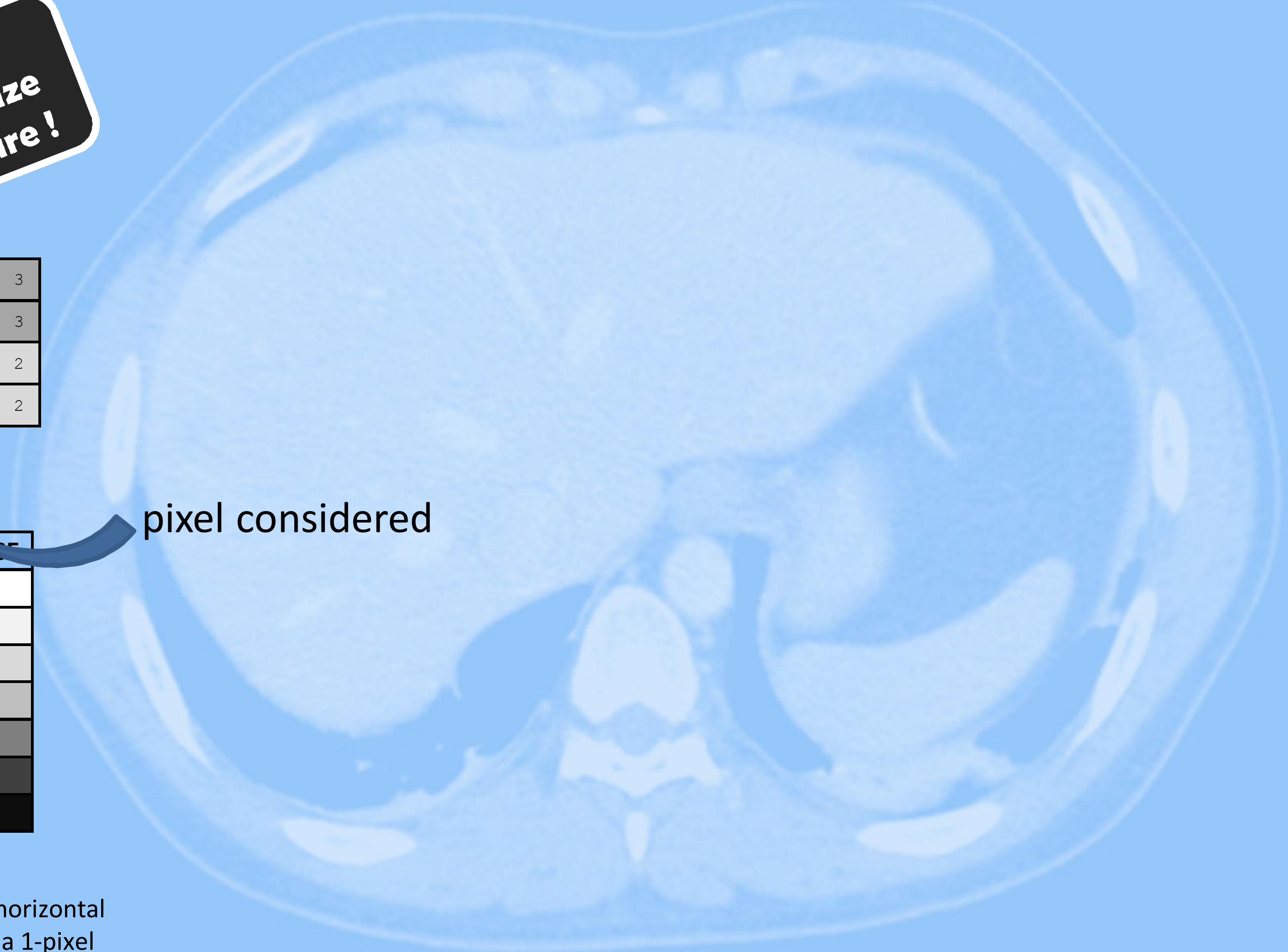
Features: Unser

Let's characterize this texture !

2	2	3	3
1	2	3	3
[illegible]	2	2	2
1	2	2	2

pixel considered

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	



Simple example: horizontal orientation from a 1-pixel right distance only

Features: Unser

Let's characterize this texture !

2	2	3	3
1	**2**	3	3
[illegible]	2	2	2
1	2	2	2

Its neighbor

pixel considered

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	

Simple example: horizontal orientation from a 1-pixel right distance only

Method

Features: Unser

Let's characterize this texture !

2	2	3	3
1	2	3	3
1	2	2	2
1	2	2	2

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	

Simple example: horizontal orientation from a 1-pixel right distance only

Unser ⇔ Haralick approximation:
Faster and as accurate

Features: Unser

Let's characterize this texture !

2	2	3	3
1	2	3	3
1	2	2	2
1	2	2	2

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	

Simple example: horizontal orientation from a 1-pixel right distance only

Unser ⇔ Haralick approximation:
Faster and as accurate

HARALICK

	0	1	2	3	4	5	6
0	0	0	0	0	0	0	0
1	0	0	**3**	0	0	0	0
2	0	**3**	**5**	**2**	0	0	0
3	0	0	**2**	**2**	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0

GreyLevel Cooccurrence Matrix (GLCM)

Method

Features: Unser

Let's characterize this texture !

2	2	3	3
1	2	3	3
1	2	2	2
1	2	2	2

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	

Simple example: horizontal orientation from a 1-pixel right distance only

Unser ⇔ Haralick approximation:
Faster and as accurate

HARALICK

	0	1	2	3	4	5	6
0	0	0	0	0	0	0	0
1	0	0	**3**	0	0	0	0
2	0	**3**	**5**	**2**	0	0	0
3	0	0	**2**	**2**	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0

GreyLevel Cooccurrence Matrix (GLCM)

Method

Features: Unser

Let's characterize this texture !

2	2	3	3
1	2	3	3
1	2	2	2
1	2	2	2

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	

Simple example: horizontal orientation from a 1-pixel right distance only

Unser ⇔ Haralick approximation: Faster and as accurate

HARALICK

UNSER

	0	1	2	3	4	5	6
0	0	0	0	0	0	0	0
1	0	0	**3**	0	0	0	0
2	0	**3**	**5**	**2**	0	0	0
3	0	0	**2**	**2**	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0

GreyLevel Cooccurrence Matrix (GLCM)

Spatial tables

4	5	6	
3	5	6	
3	4	4	
3	4	4	

Sum

	0	1	0
	1	1	0
	1	0	0
	1	0	0

Difference

Method

Features: Unser

Let's characterize this texture !

2	2	3	3
1	2	3	3
1	2	2	2
1	2	2	2

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	

Simple example: horizontal orientation from a 1-pixel right distance only

Unser ⇔ Haralick approximation:
Faster and as accurate

UNSER

HARALICK

	0	1	2	3	4	5	6
0	0	0	0	0	0	0	0
1	0	0	**3**	0	0	0	0
2	0	**3**	**5**	**2**	0	0	0
3	0	0	**2**	**2**	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0

GreyLevel Cooccurrence Matrix (GLCM)

Spatial tables

4	5	6	
3	5	6	
3	4	4	
3	4	4	

Sum

	0	1	0
	1	1	0
	1	0	0
	1	0	0

Difference

Method

Features: Unser

Let's characterize this texture !

2	2	3	3
1	2	3	3
1	2	2	2
1	2	2	2

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	

Simple example: horizontal orientation from a 1-pixel right distance only

Unser ⇔ Haralick approximation: Faster and as accurate

HARALICK

	0	1	2	3	4	5	6
0	0	0	0	0	0	0	0
1	0	0	**3**	0	0	0	0
2	0	**3**	**5**	**2**	0	0	0
3	0	0	**2**	**2**	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0

GreyLevel Cooccurrence Matrix (GLCM)

UNSER

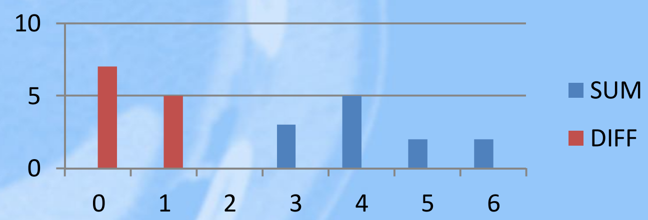
Spatial tables

4	5	6	
3	5	6	
3	4	4	
3	4	4	

Sum

	0	1	0
	1	1	0
	1	0	0
	1	0	0

Difference



Sum & Difference histograms

Features: Unser

Let's characterize this texture !

2	2	3	3
1	2	3	3
1	2	2	2
1	2	2	2

PIXEL RANGE	
0	
1	
2	
3	
4	
5	
6	

Simple example: horizontal orientation from a 1-pixel right distance only

Unser ⇔ Haralick approximation:
Faster and as accurate

HARALICK

UNSER

	0	1	2	3	4	5	6
0	0	0	0	0	0	0	0
1	0	0	**3**	0	0	0	0
2	0	**3**	**5**	**2**	0	0	0
3	0	0	**2**	**2**	0	0	0
4	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0

GreyLevel Cooccurrence Matrix (GLCM)

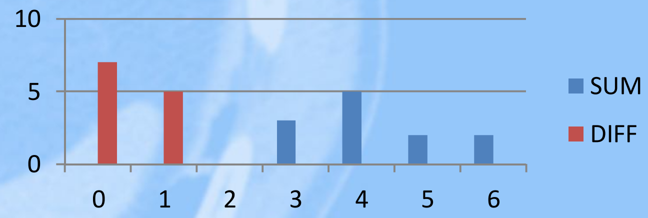
Spatial tables

4	5	6	
3	5	6	
3	4	4	
3	4	4	

Sum

	0	1	0
	1	1	0
	1	0	0
	1	0	0

Difference



Sum & Difference histograms

14

Statistic measures computation

9

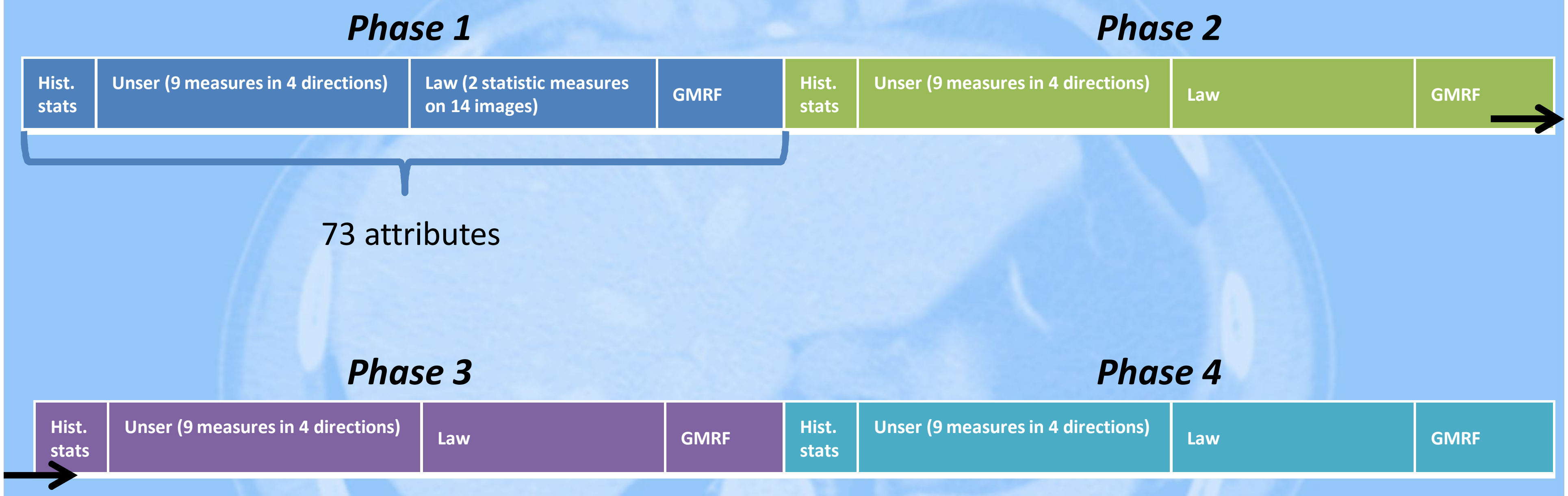
Feature Vector

Phase 1

Hist. stats	Unser (9 measures in 4 directions)	Law (2 statistic measures on 14 images)	GMRF

73 attributes

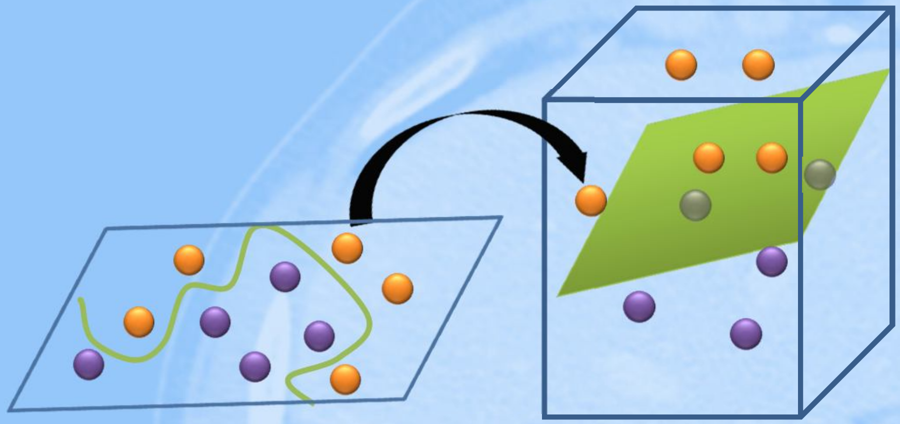
Feature Vector



TOTAL: 292 attributes

Classification algorithm

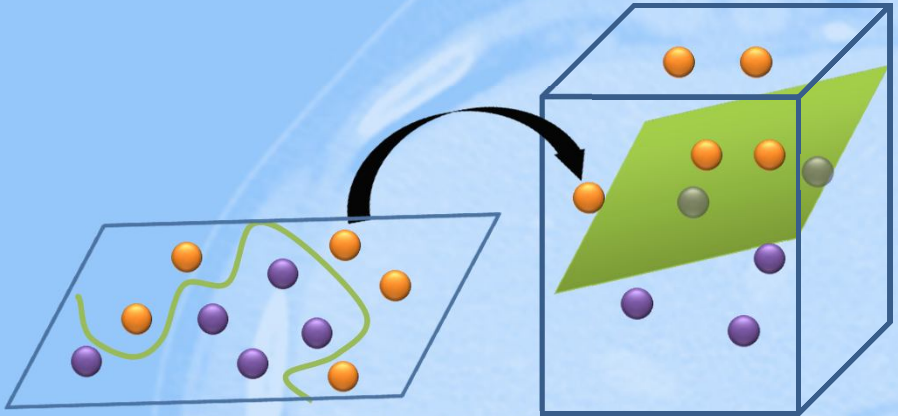
Support Vector Machine (SVM)



Let's get in a higher dimensional space !

Classification algorithm

Support Vector Machine (SVM)



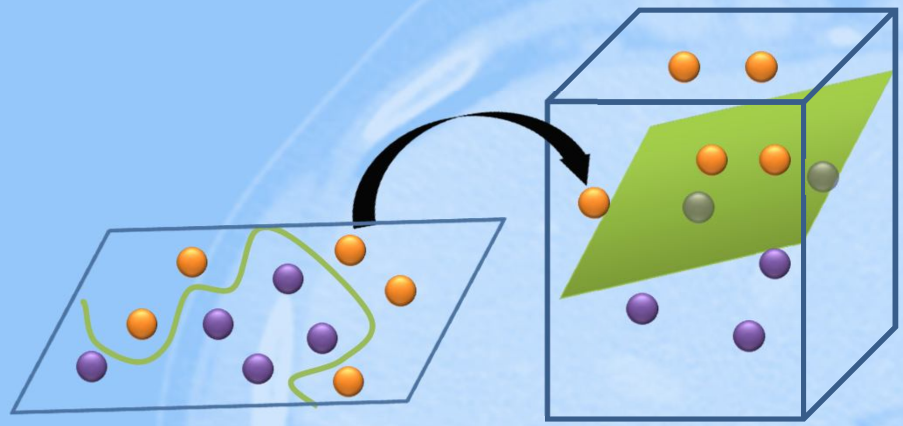
Let's get in a higher dimensional space !

Implementation:
Sequential Minimal Optimization [1]

1 Platt J., *Fast Training of Support Vector Machines Using Sequential Minimal Optimization*, Advances in Kernel Methods - Support Vector Learning, MIT Press 2007

Classification algorithm

Support Vector Machine (SVM)



Let's get in a higher dimensional space !

Implementation:
Sequential Minimal Optimization [1]

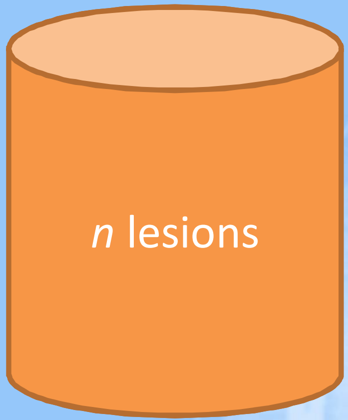
Parameters: Polynomial kernel. Exponent tested from 1 to 6, best kept (as in [2])

1 Platt J., *Fast Training of Support Vector Machines Using Sequential Minimal Optimization*, Advances in Kernel Methods - Support Vector Learning, MIT Press 2007

2 Duda D., Kretowski M., Bezy-Wendling J., *Texture Characterization for Hepatic Tumor Recognition in Multiphase CT*, Biocybernetics and Biomedical Engineering, vol. 26(4), p. 15-24, 2006.

Classification evaluation

Leave One Out Cross-validation



Classification evaluation

Leave One Out Cross-validation

n lesions

Cross-validation

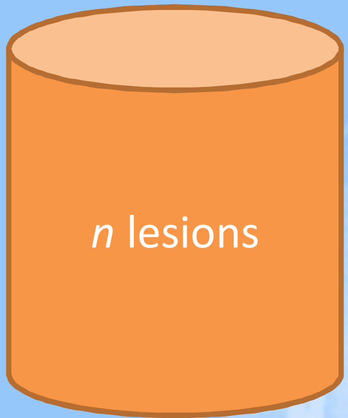
1. Split the database in learning and testing data

2. Classify and evaluate results

3. Go to *1.* and do it again for different partitions

Classification evaluation

Leave One Out Cross-validation



Cross-validation

1. Split the database in learning and testing data

2. Classify and evaluate results

3. Go to *1.* and do it again for different partitions

Leave One Out (LOO)

- only 1 test lesion
- *n*-1 learning lesions

Exhaustive:
n different partitions

Layout

- Introduction
- Data
- Method
- **Results**
  - **Precision & Recall**
  - **Confusion matrices**
- Comparison
- Conclusion

Precision & Recall 1/2

Precision

- Measure of the accuracy
- Provided that a specific class has been predicted

$$\text{Precision} = \frac{\textbf{Number of lesions correctly labelled } \boldsymbol{i}}{\textbf{Number of lesions labelled } \boldsymbol{i}}$$

i a given class

Precision & Recall 1/2

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- Measure of the ability to select instances of a certain class
- from a data set

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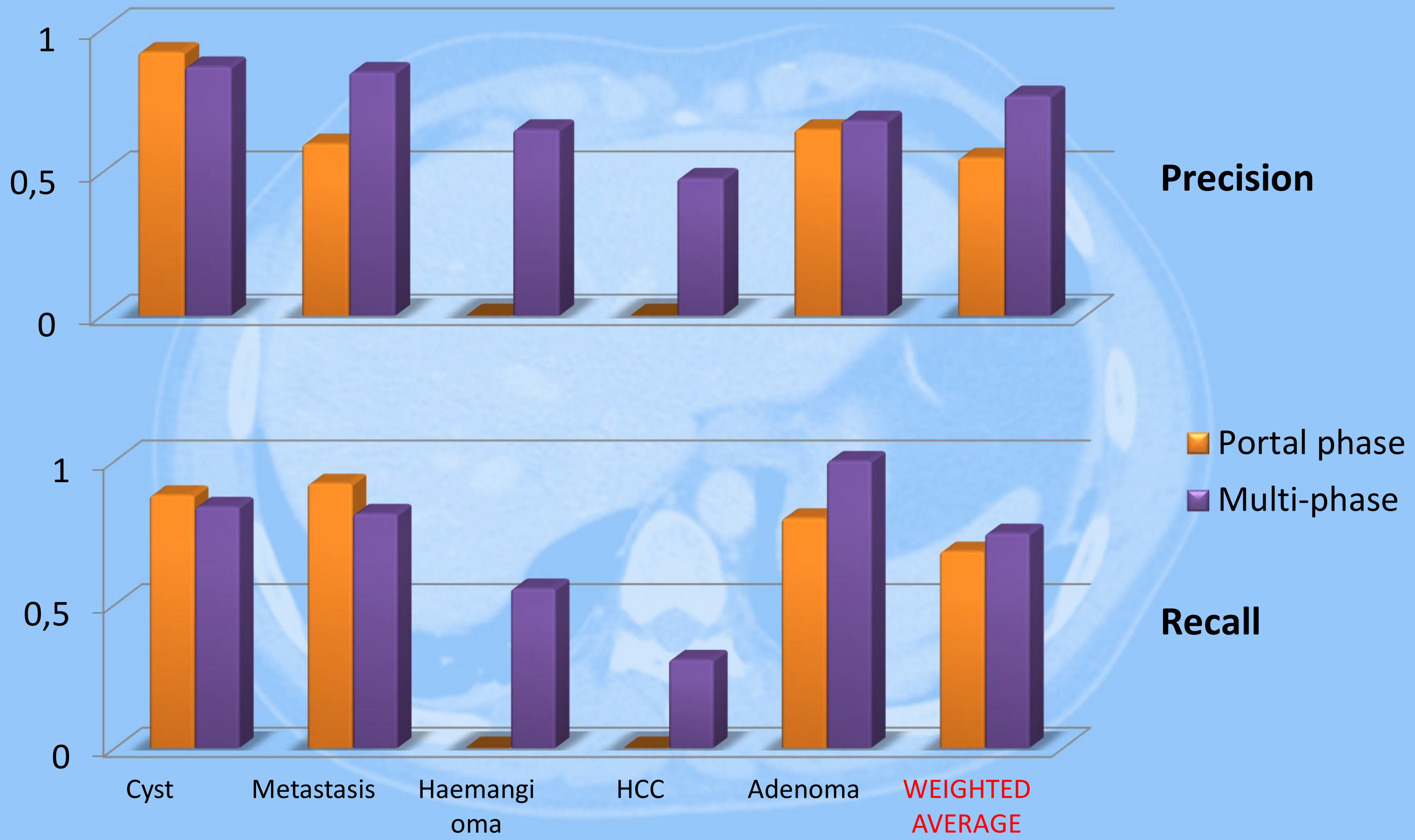
Range [0 1] with 1.00 the best

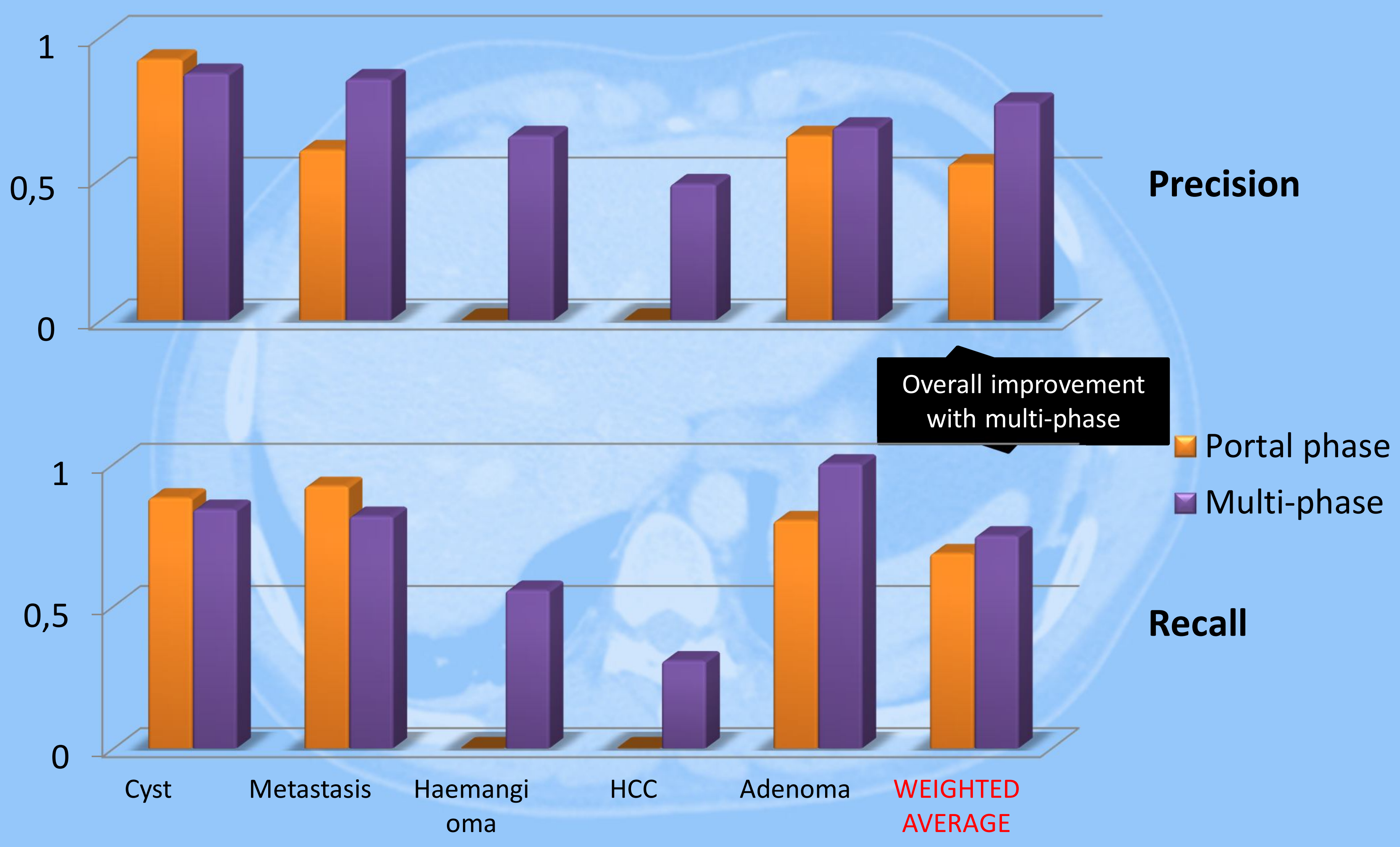
Results

Precision & Recall 2/2



Results

Precision & Recall 2/2



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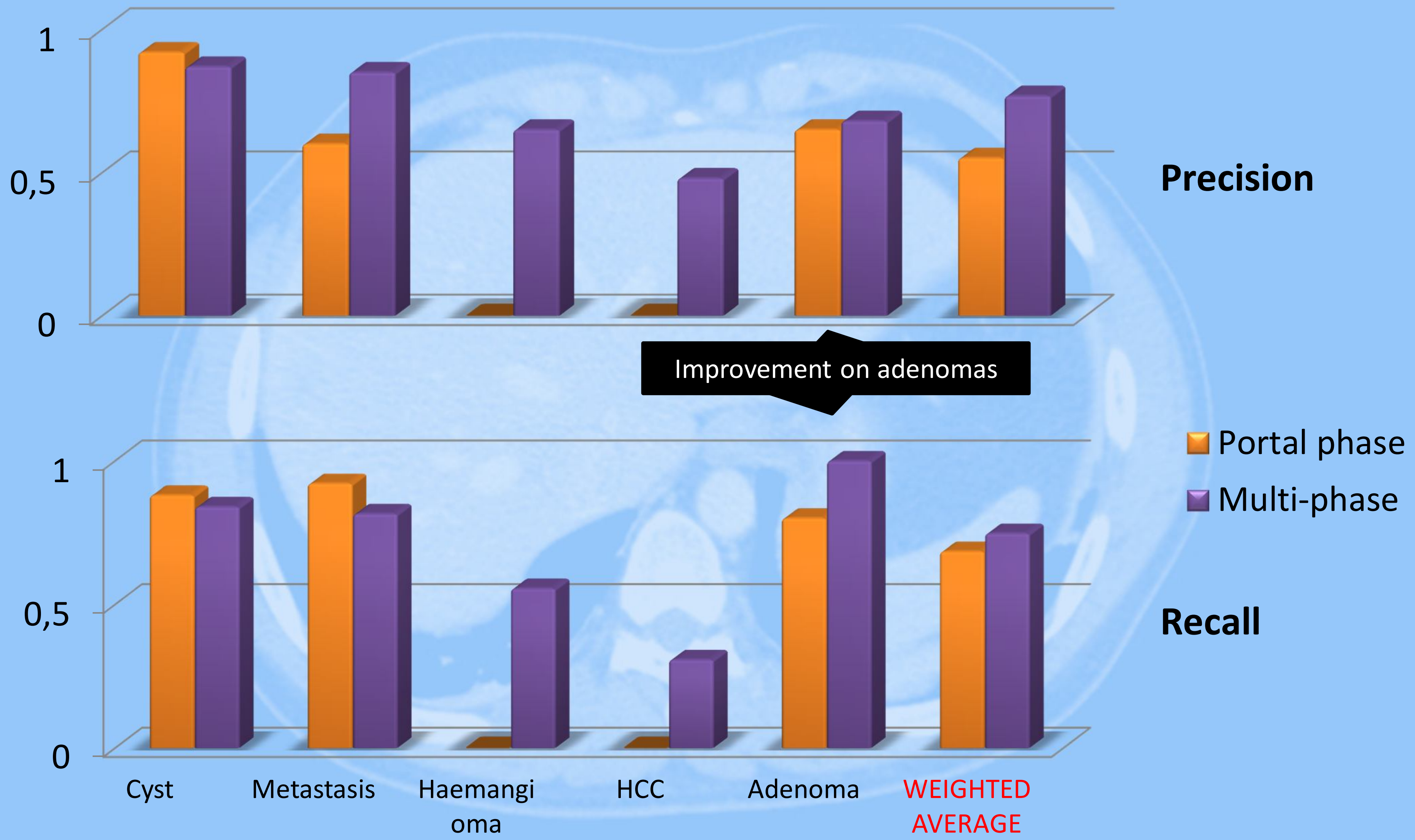
Precision & Recall 2/2



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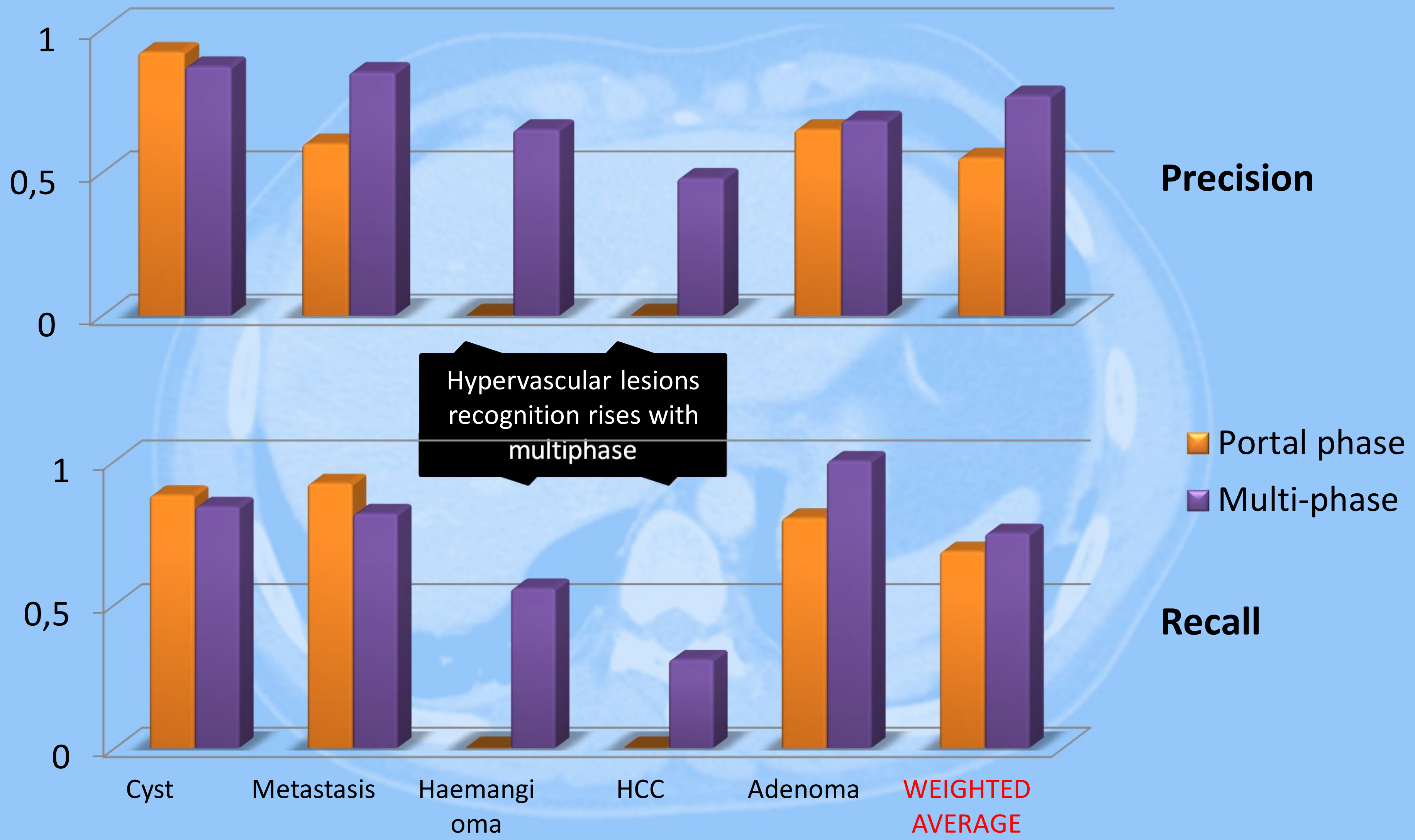
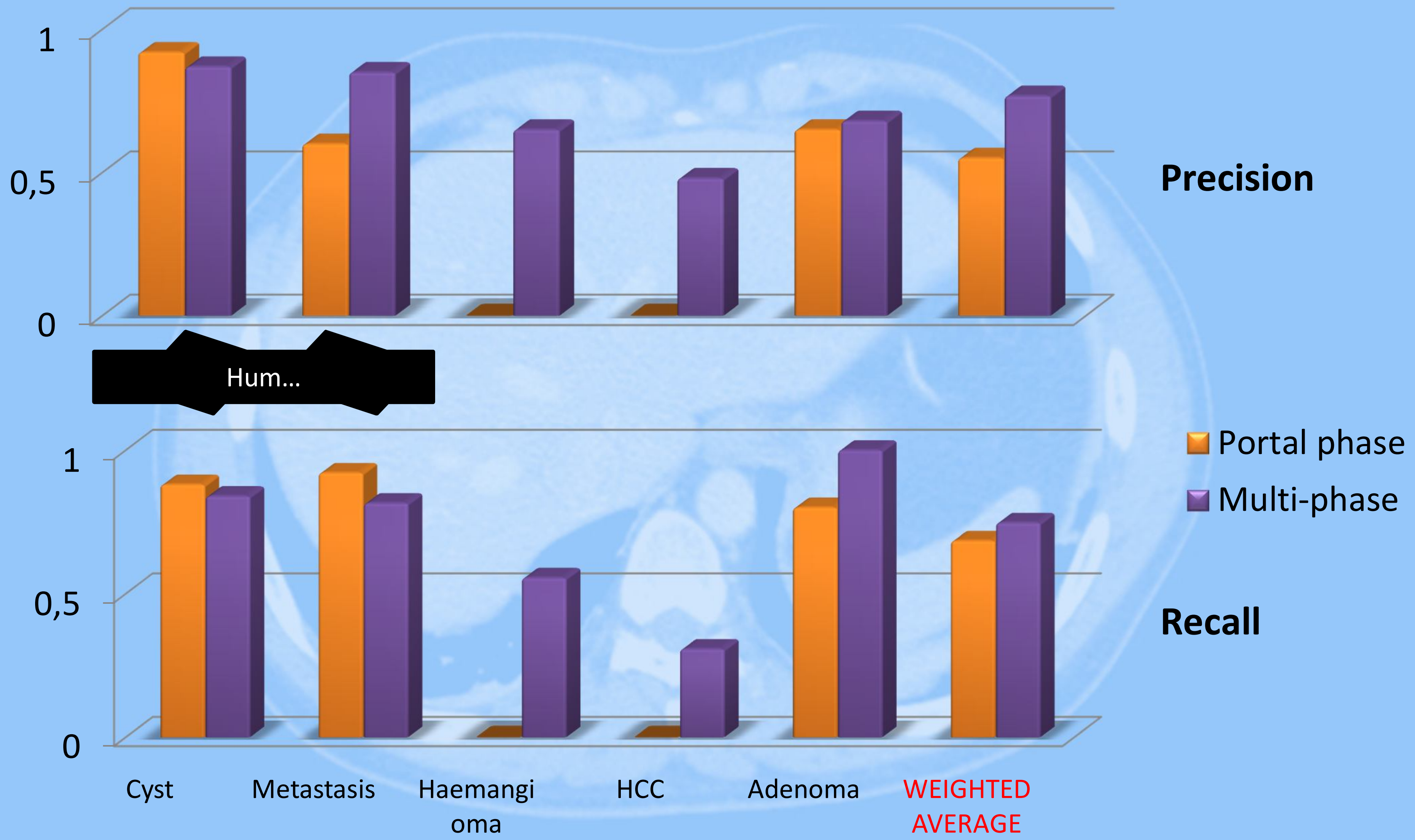


Precision & Recall 2/2



Confusion matrices

PORTAL PHASE

	Cyst	Ade.	Hae.	HCC	Met.
Cyst	**22**	1	1	0	1
Ade.	0	**8**	0	0	2
Hae.	0	3	**0**	0	6
HCC	0	0	0	**0**	13
Met.	2	1	0	0	**35**

MULTI-PHASE

	Cyst	Ade.	Hae.	HCC	Met.
Cyst	**21**	3	0	0	1
Ade.	0	**10**	0	0	0
Hae.	1	0	**5**	3	0
HCC	0	0	2	**4**	7
Met.	3	2	1	1	**31**

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Multi-phase effects

- **overall improvement**
- very good influence **on hypervascular lesions,** and in slight proportion on adenomas
- **cysts and metastasis are stable**

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Metastasis problem:

its visual aspect may look like any other kind of lesion !

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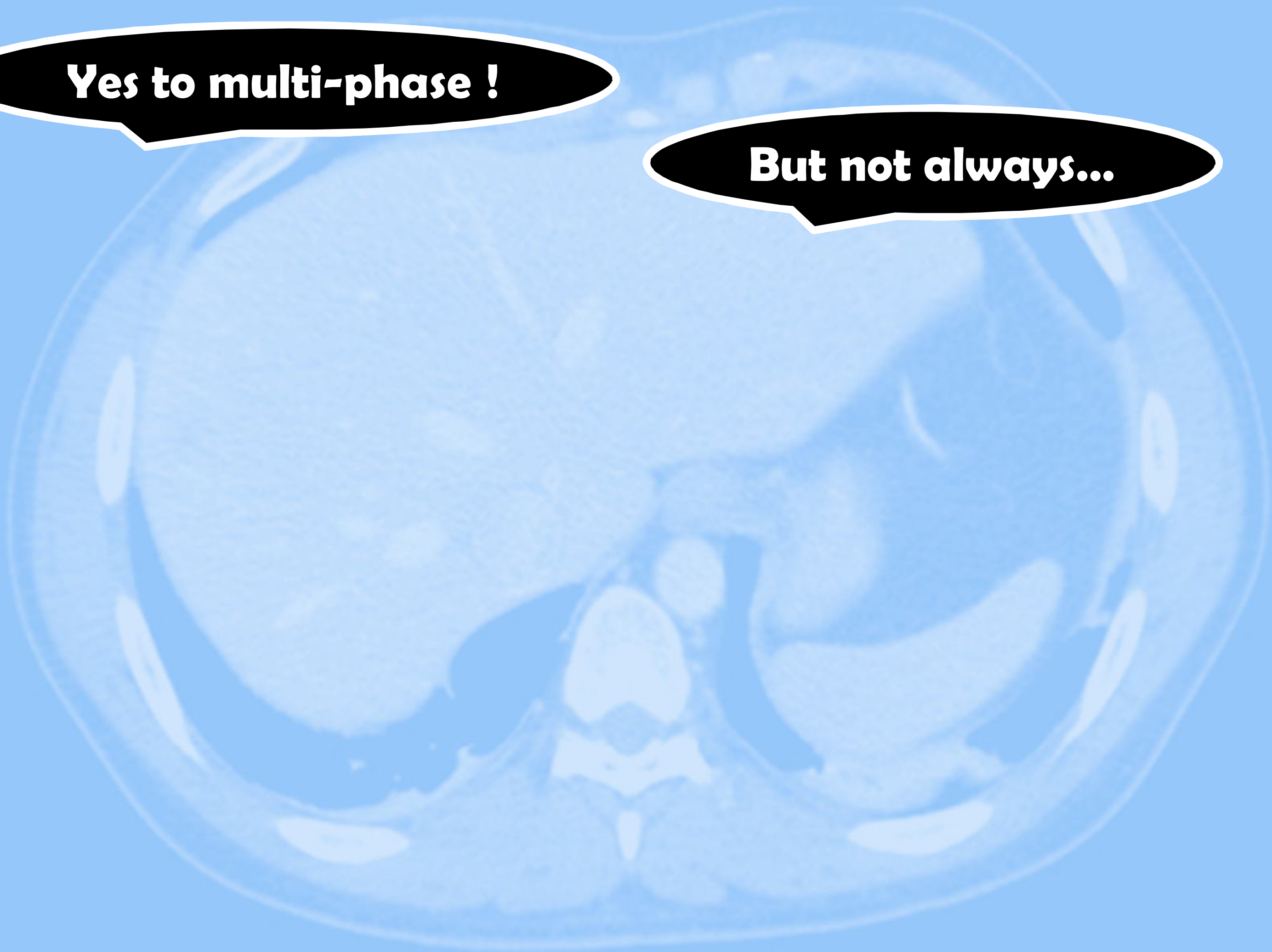
Multi-phase helps reducing the number of lesions mislabelled as metastasis.

But the results are spread out on the other axis.

Discussion

Discussion



Discussion

Yes to multi-phase !

But not always…

1. Two-step classification ?

- cysts / metastasis / other ***on portal phase ?***
- haemangioma / HCC ***on multi-phase***

Discussion

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2. It's time to increase the size of our database

Layout

- Introduction
- Data
- Method
- Results
- **Comparison**
  - Overview
  - Data
  - Method
  - Experiment
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Overview

How do we perform compared to others ?

Comparison

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Only a few Computer Aided Diagnosis systems working on hepatic multi-phase CT scans

Comparison

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2 Duda D., Kretowski M., Bezy-Wendling J., *Texture Characterization for Hepatic Tumor Recognition in Multiphase CT*, Biocybernetics and Biomedical Engineering, vol. 26(4), p.15-24, 2006.

3 M. Ishiguro, I. Murase, N. Moriyama and R. Sekiguchi, *A Classification Method of Liver Tumors based on Temporal Change of Hounsfield Unit in CT Images*, Proceedings of SPIE Medical Imaging, V. 5747, p. 822-830, 2005

Expertise

Comparison - data

Characteristics	Ye. Et al [1]	Duda et al. [2]	Our work
Lesion number	131	165	95
Phases	4	3	2 to 4
Diagnosis classes	healthy, HCC, cyst, haemangioma	healthy, HCC, cholangiocarcinoma	adenoma, cyst, haemangioma, HCC, metastasis
Region Of Interest	16*16 pixels square	30 to 70 pixels radii circle	from 9*12 to 165*180 pixels rectangle
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Comparison - method

Characteristics		Ye. Et al [1]	Duda et al. [2]	Our work
Fea-tures	Grey levels	First Order Statistics		
	Texture	Co-occurrence	Co-occurrence + Law + Run-length	Unser + Law + GMRF
	Time	Temporal features	-	-
Classifier		SVM		
Classification		3 binomial sequential classifications: -Healthy vs pathological -If pathological: cyst vs non-cyst -If non-cyst: HCC vs haemangioma	Distinguish the 3 classes	Distinguish the 5 classes

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	Time	Temporal features	-	-
Classifier		SVM		
Classification		3 binomial sequential classifications on each phase: -Healthy vs pathological -If pathological: cyst vs non-cyst -If non-cyst: HCC vs haemangioma	Distinguish the 3 classes on multi-phase	Distinguish the 5 classes on multi-phase

Comparison

Experiment

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49 lesions from 41 patients

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Healthy liver	cyst	haemangioma	HCC
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Ye feature sets: histogram statistics, GLCM, Temporal
Our feature sets: histogram statistics, Unser, Law, GMRF, Temporal

Comparison

Experimental Results

Results: All features

Phase	Ye et al. work			Our work		
	Healthy vs unhealthy	Cyst vs others	HCC vs haemangioma	Healthy vs unhealthy	Cyst vs others	HCC vs haemangioma
Pre contras.	0.92	0.97	0.89	0.98	0.73	0.79
Arterial	0.91	0.97	0.96	0.88	0.84	0.89
Portal	0.95	0.97	0.96	0.94	0.95	0.68
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All	-	-	-	0.98	0.95	0.74

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Comparison

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But may be heterogeneous
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3. Phase by phase analysis is necessary

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Multi-phase

Multi-phase needs to be introduced in order to take into account the enhancement information.

Multi-phase

Multi-phase needs to be introduced in CAD hepatic systems order to take into account the enhancement information.

How ? With all phases at a time ? Depending on the lesion type ? Depending on the features ?

=> Extended analysis is to be done.

Data

Database size should be increased

in order to validate the results

(done by now: over 200 ROIs – healthy and 8 diagnosis classes)

Visual features

- New applied feature: Unser histograms
- Actual set gives promising results
- Selection
- Explore temporal features

Conclusion

Perspectives

Conf. article submitted

Let's see what radiologists can do !

OsiriX DICOM viewer

open source