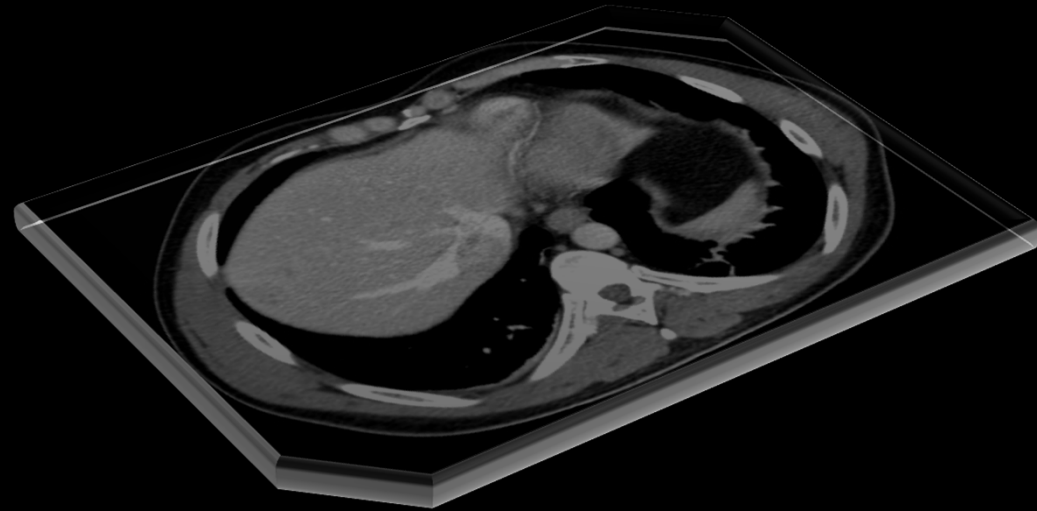


Liver Lesion Classification on Multi-Phase CT



**Auréline Quatrehomme^{1,2}, Ingrid Millet³,
Denis Hoa¹, Gérard Subsol², William Puech²**



¹ IMAIOS www.imaios.com

² Montpellier 2 Univ. / CNRS - LIRMM

³ University Hospital of Montpellier

*Montpellier,
FRANCE*



Layout

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



Introduction

Context

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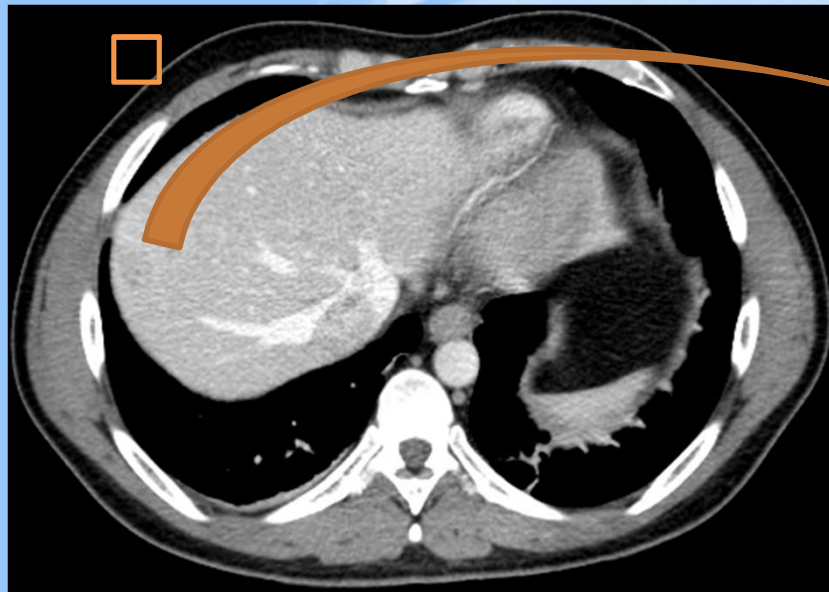
www.imaios.com

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



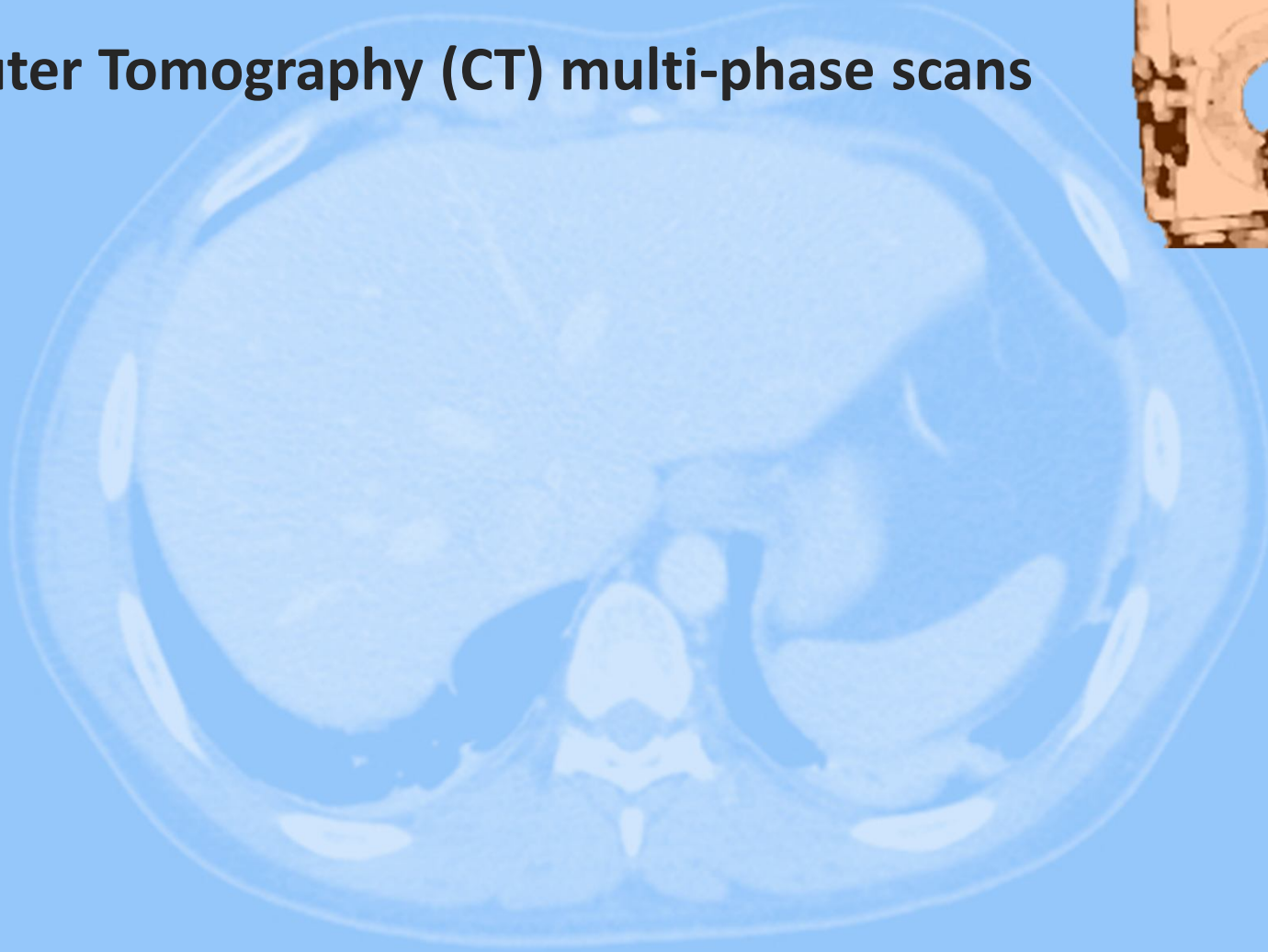
Retrospective analysis of cases

[2008 – 2011]

Data

Multi-phase CT scans

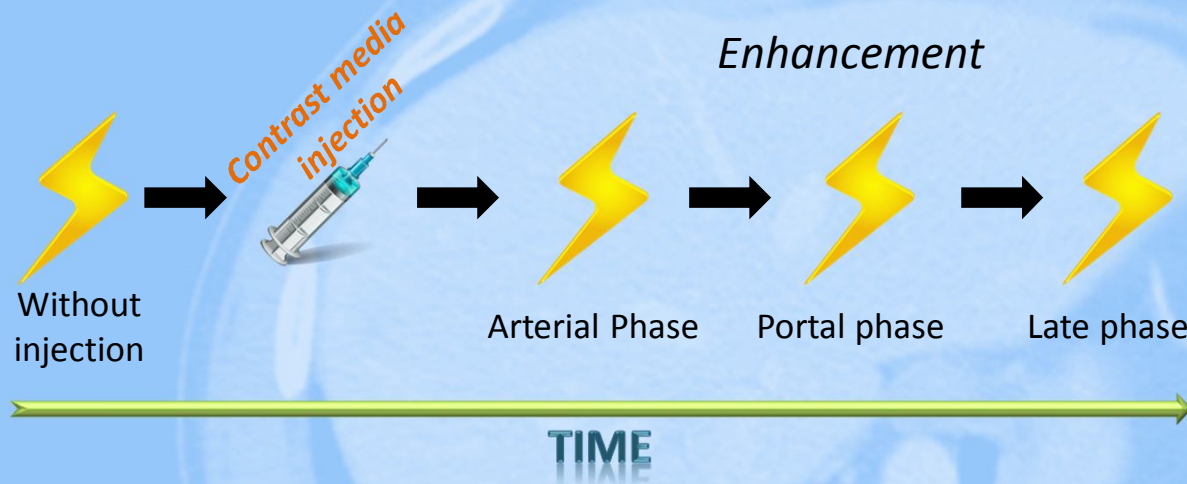
Computer Tomography (CT) multi-phase scans



Data

Multi-phase CT scans

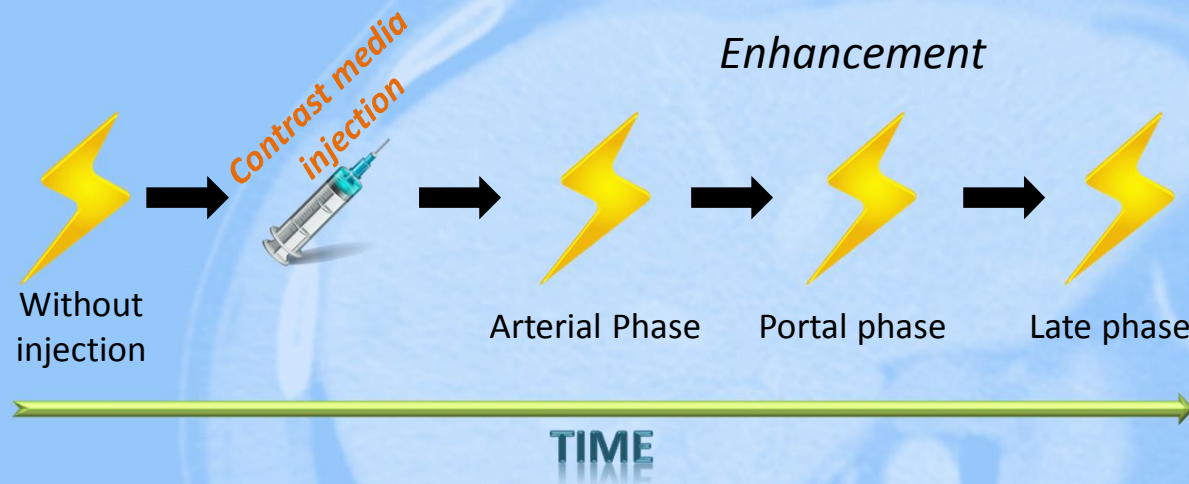
Computer Tomography (CT) multi-phase scans



Data

Multi-phase CT scans

Computer Tomography (CT) multi-phase scans

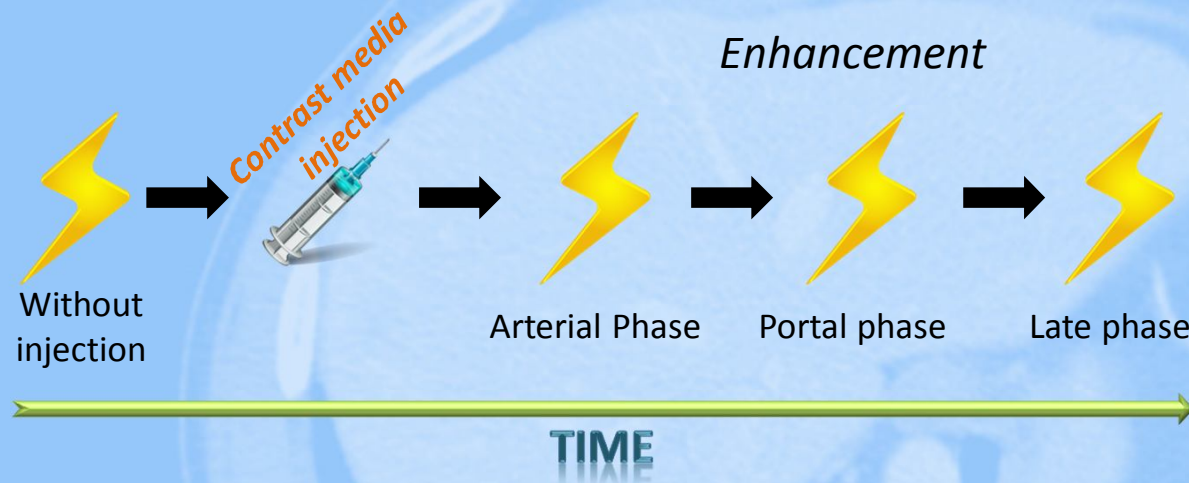


4 series of 2D  slices

Data

Multi-phase CT scans

Computer Tomography (CT) multi-phase scans



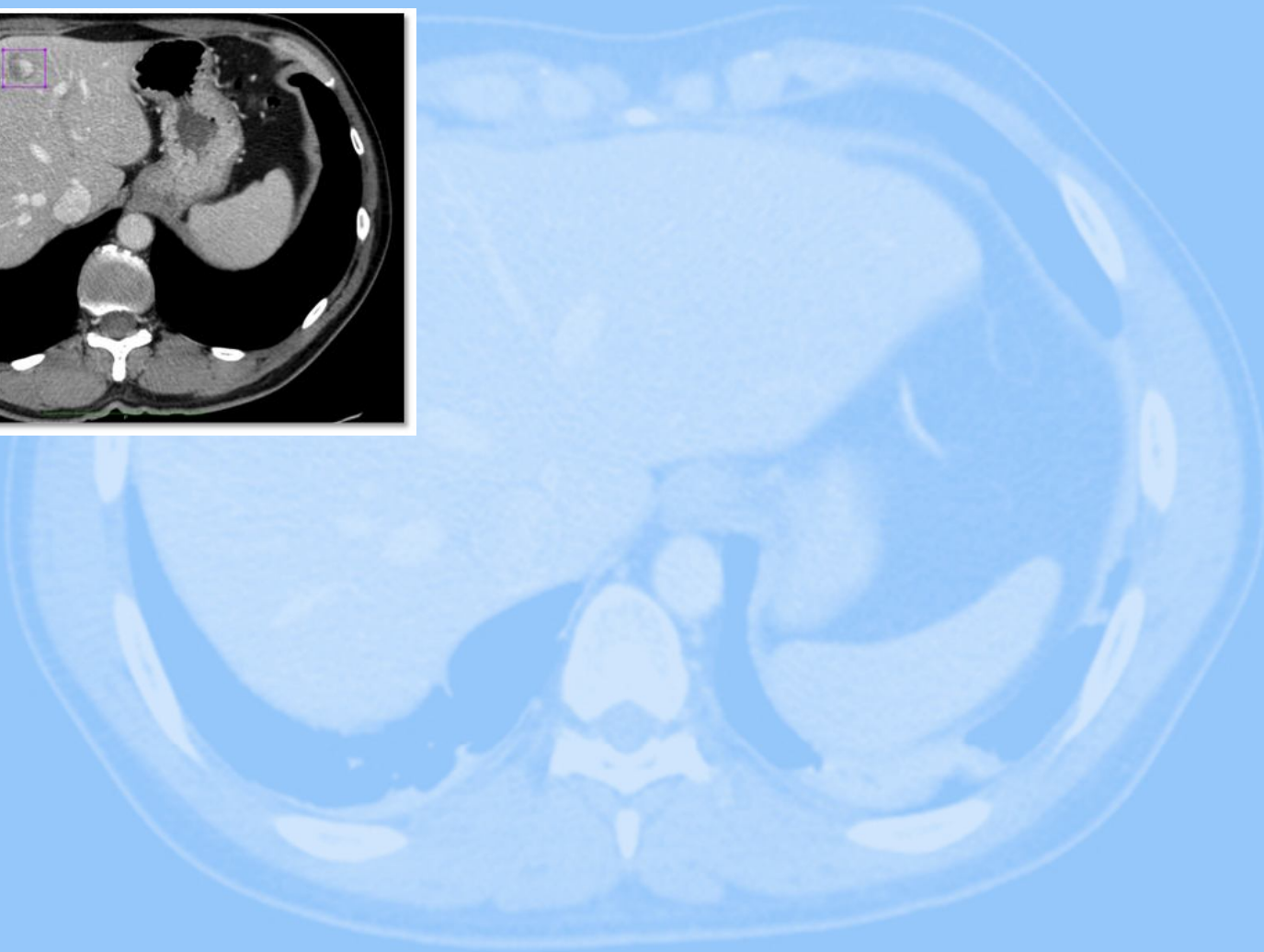
Essential to radiologists to make a diagnosis
But almost absent from CAD hepatic systems



4 series of 2D  slices

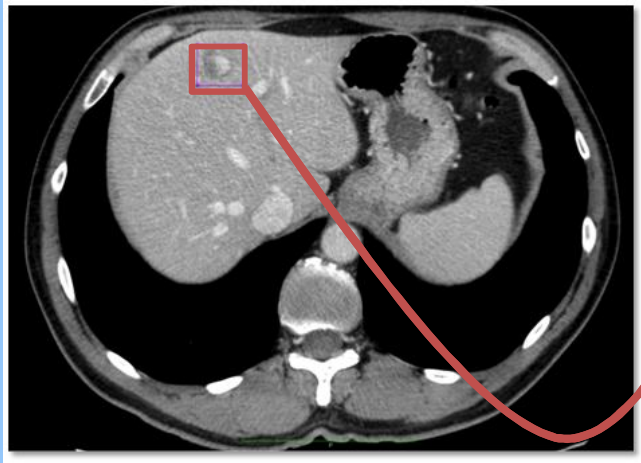
Data

Region Of Interest (ROI)

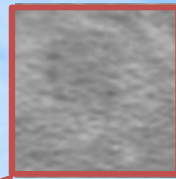


Data

Region Of Interest (ROI)

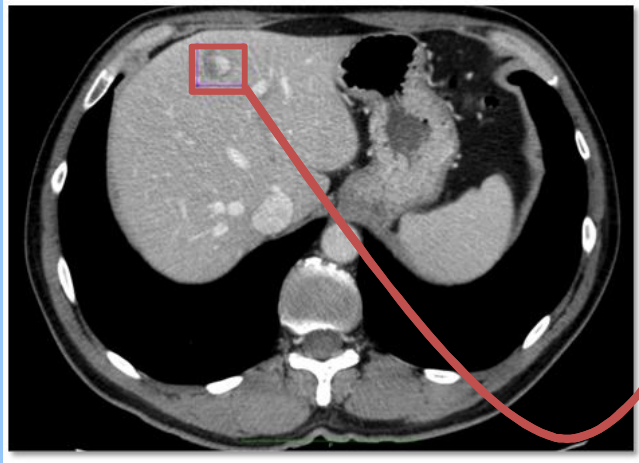


Manual rectangular ROI

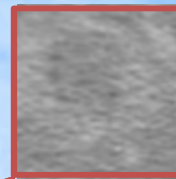


Data

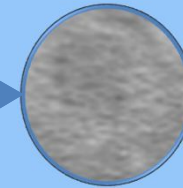
Region Of Interest (ROI)



Manual rectangular ROI

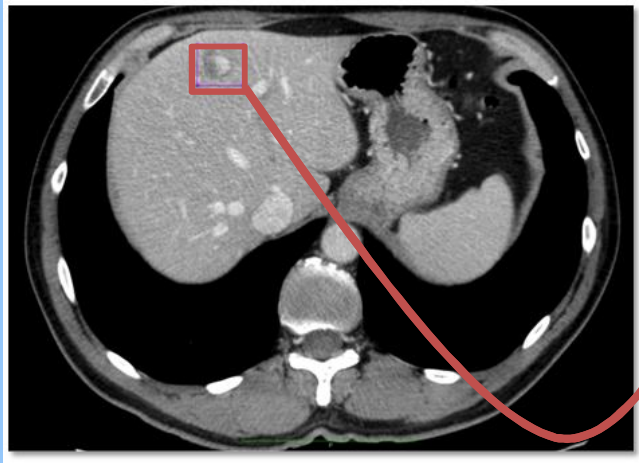


Automatic ellipse extraction

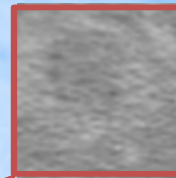


Data

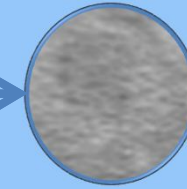
Region Of Interest (ROI)



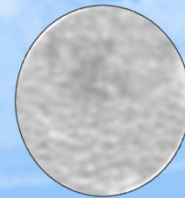
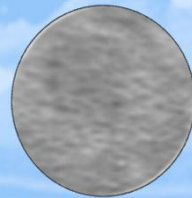
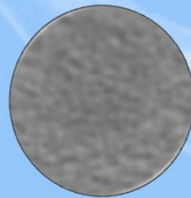
Manual rectangular ROI



Automatic ellipse extraction





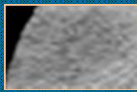

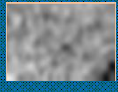







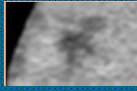

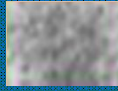





1 lesion \Leftrightarrow 4 * 2D ROIs (1 by phase)



Data

Database

95 lesions from 40 patients

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

* HepatoCellular Carcinoma

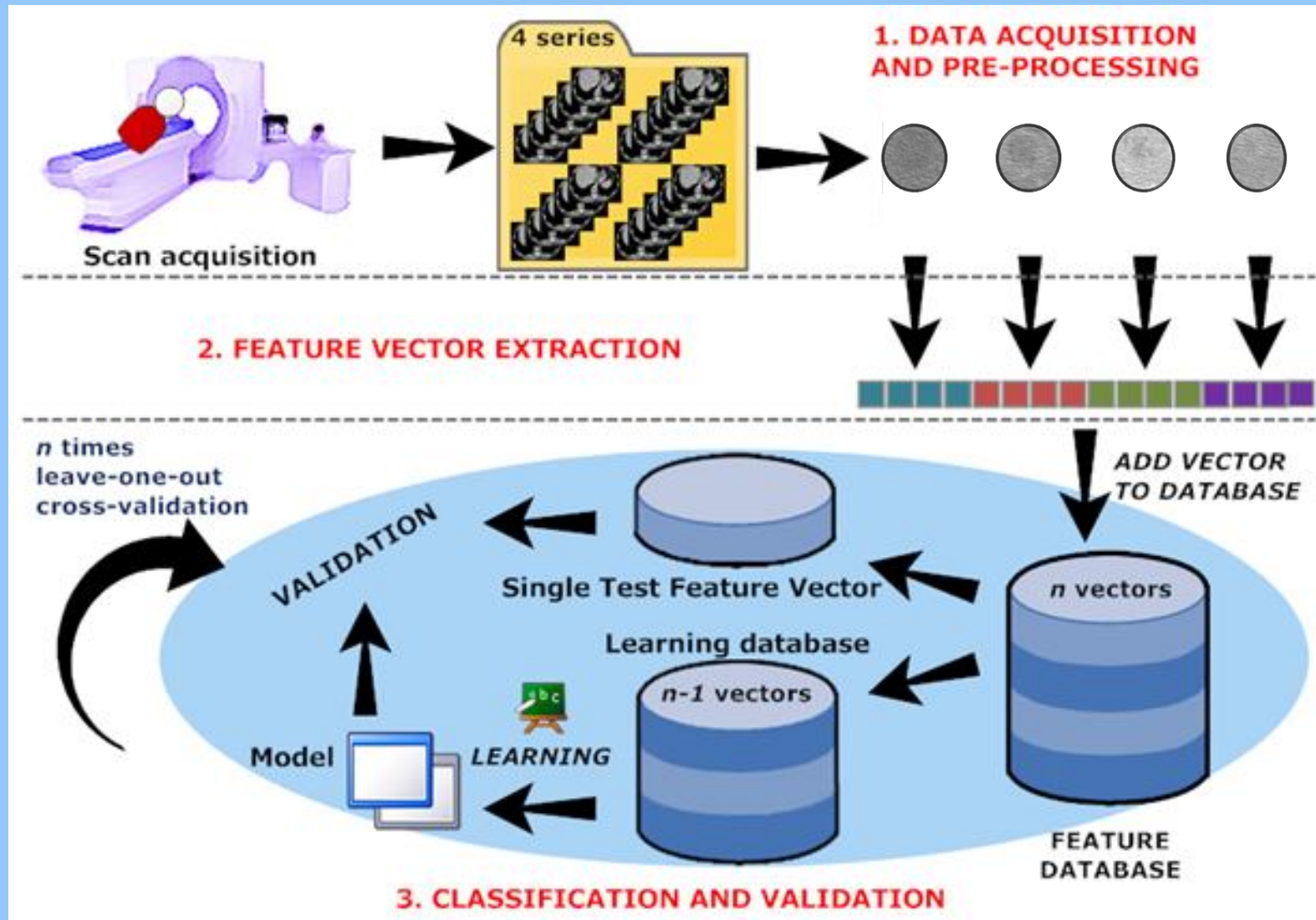
Layout

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



Method

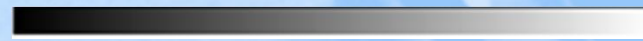
Framework



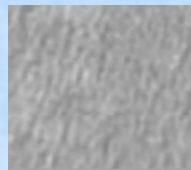
Features - generalities

They describe:

- the grey levels / color



- the texture



- the shape

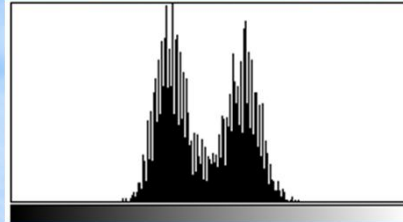


in an image

Feature list

Visual descriptors in our system

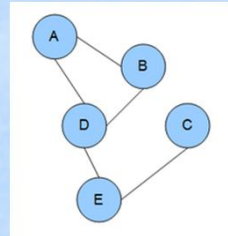
Histogram first order statistics



Statistics computed over the grey-level histogram



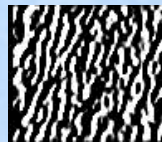
Gaussian Markov Random Fields (GMRF)



[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

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

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.

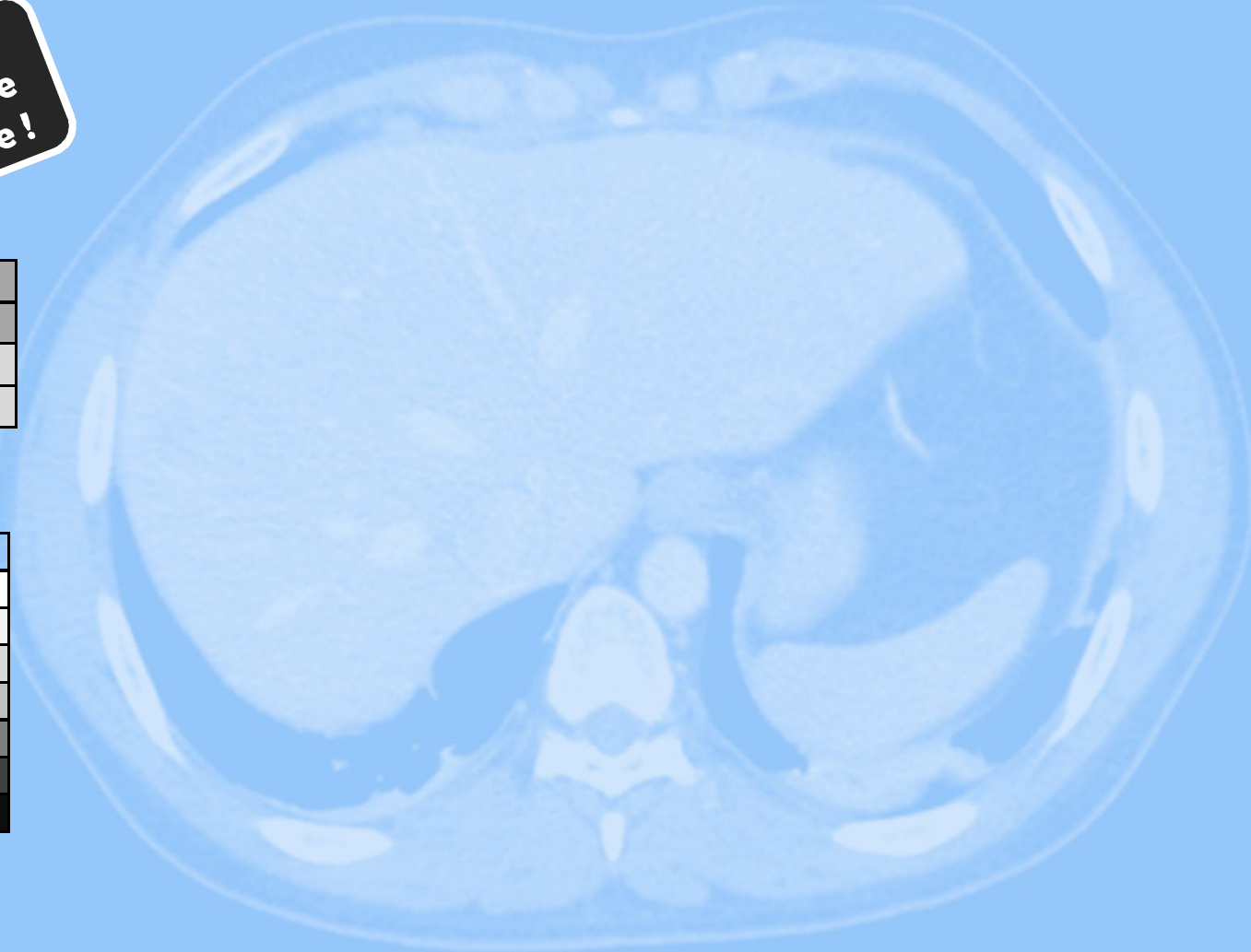
Method

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	










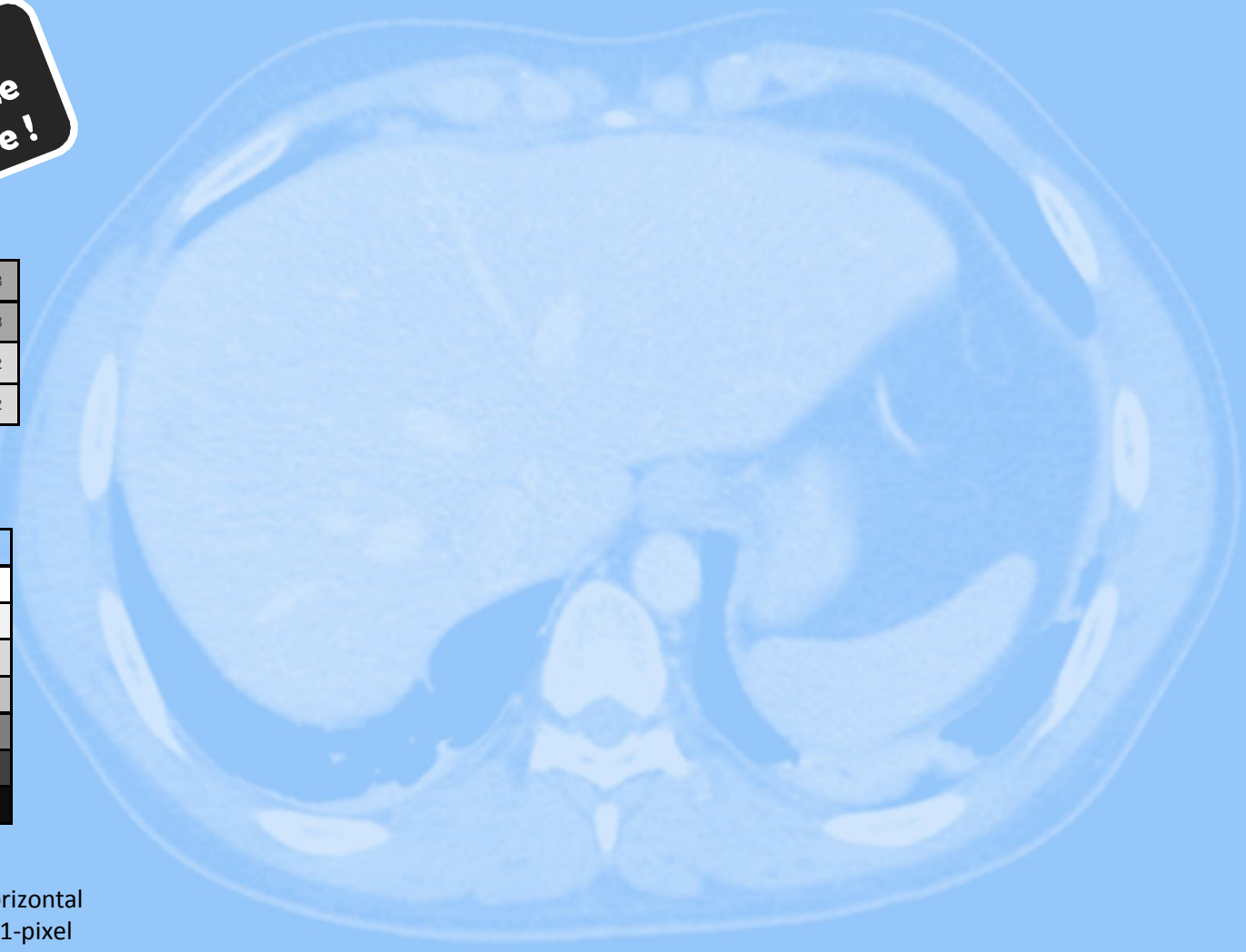
Method

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	



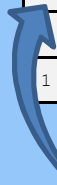
Simple example: horizontal orientation from a 1-pixel right distance only

Method

Features: Unser

Let's characterize this texture!

2	2	3	3
1	2	3	3
	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

Method

Features: Unser

Let's characterize this texture!

2	2	3	3
1	2	3	3
	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

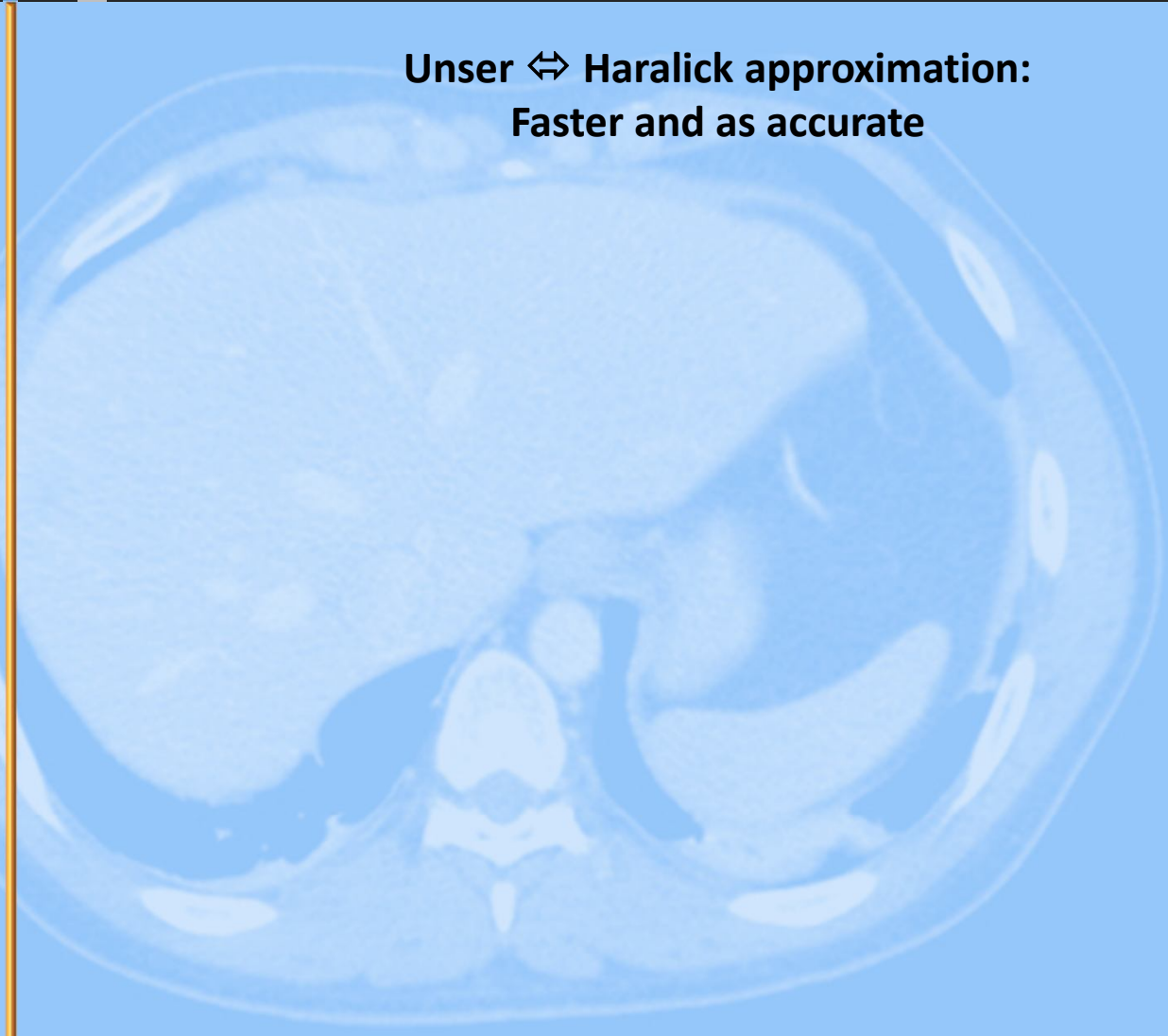
Let's characterize this texture!

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 \Leftrightarrow Haralick approximation:
Faster and as accurate



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 \Leftrightarrow 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

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 ↔ Haralick approximation:
Faster and as accurate

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

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

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 ↔ Haralick approximation:
Faster and as accurate

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

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

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 ↔ Haralick approximation:
Faster and as accurate

UNSER

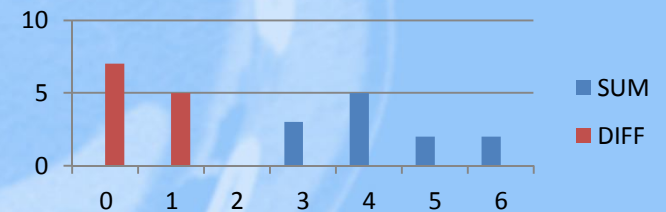
Spatial tables

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

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

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 \leftrightarrow Haralick approximation:
Faster and as accurate

UNSER

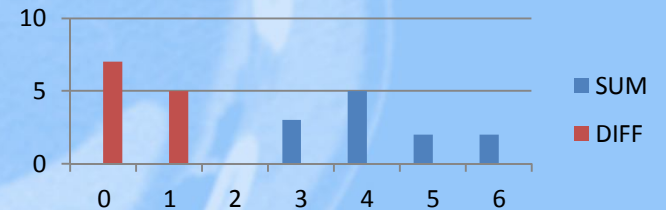
Spatial tables

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

14

Statistic measures computation

9

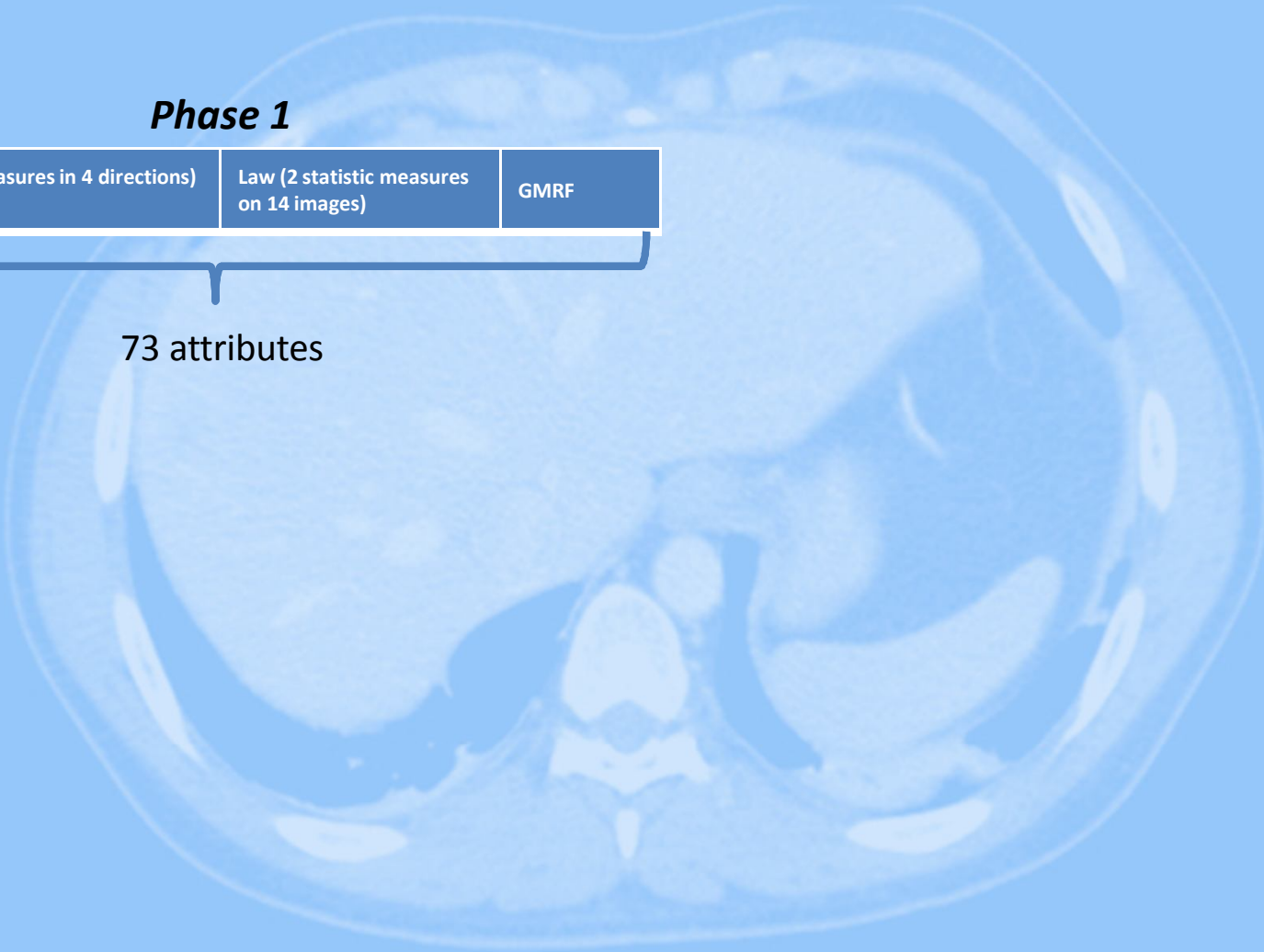
Method

Feature Vector

Phase 1

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

73 attributes

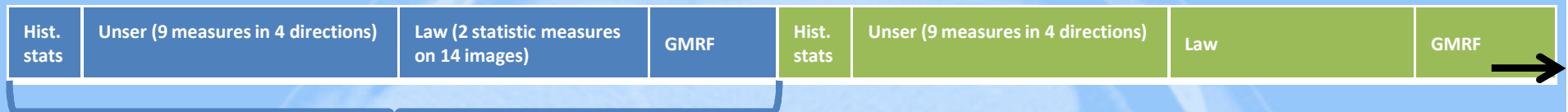


Method

Feature Vector

Phase 1

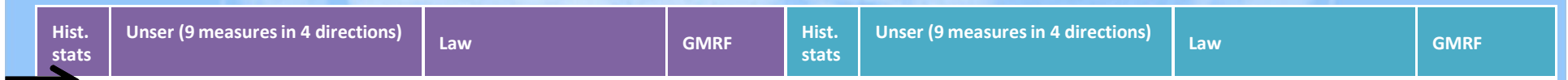
Phase 2



73 attributes

Phase 3

Phase 4

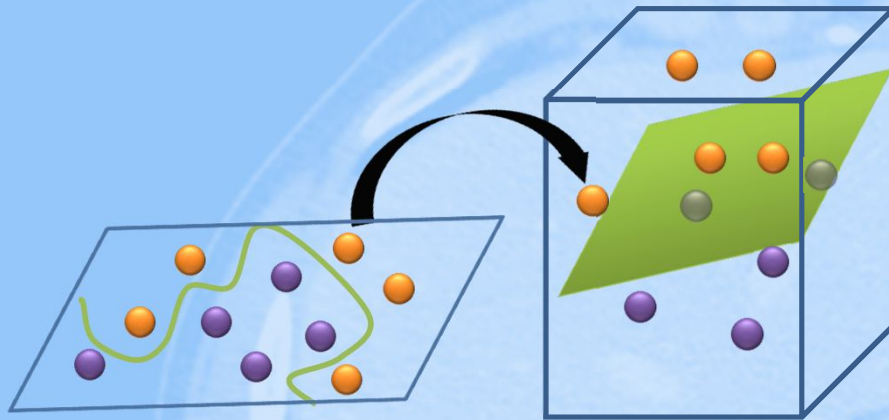


TOTAL: 292 attributes

Method

Classification algorithm

Support Vector Machine (SVM)

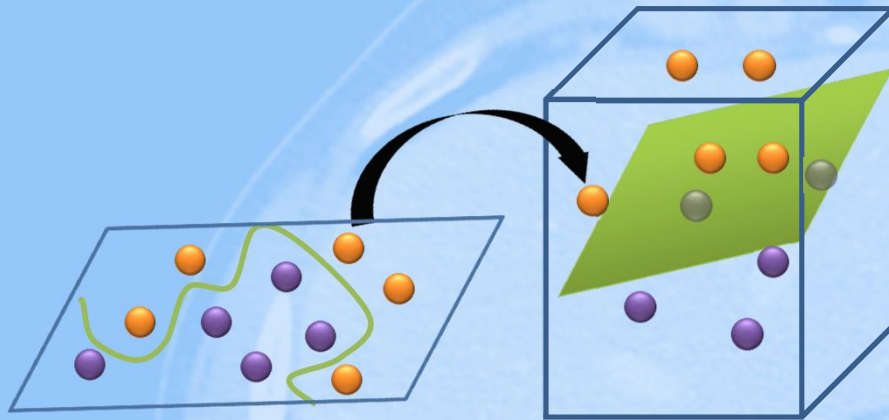


Let's get in a higher dimensional space !

Method

Classification algorithm

Support Vector Machine (SVM)



Let's get in a higher dimensional space !



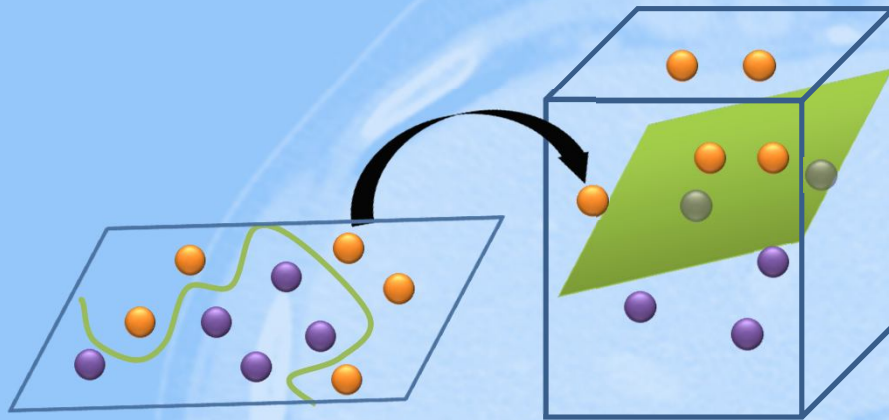
Implementation:

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])

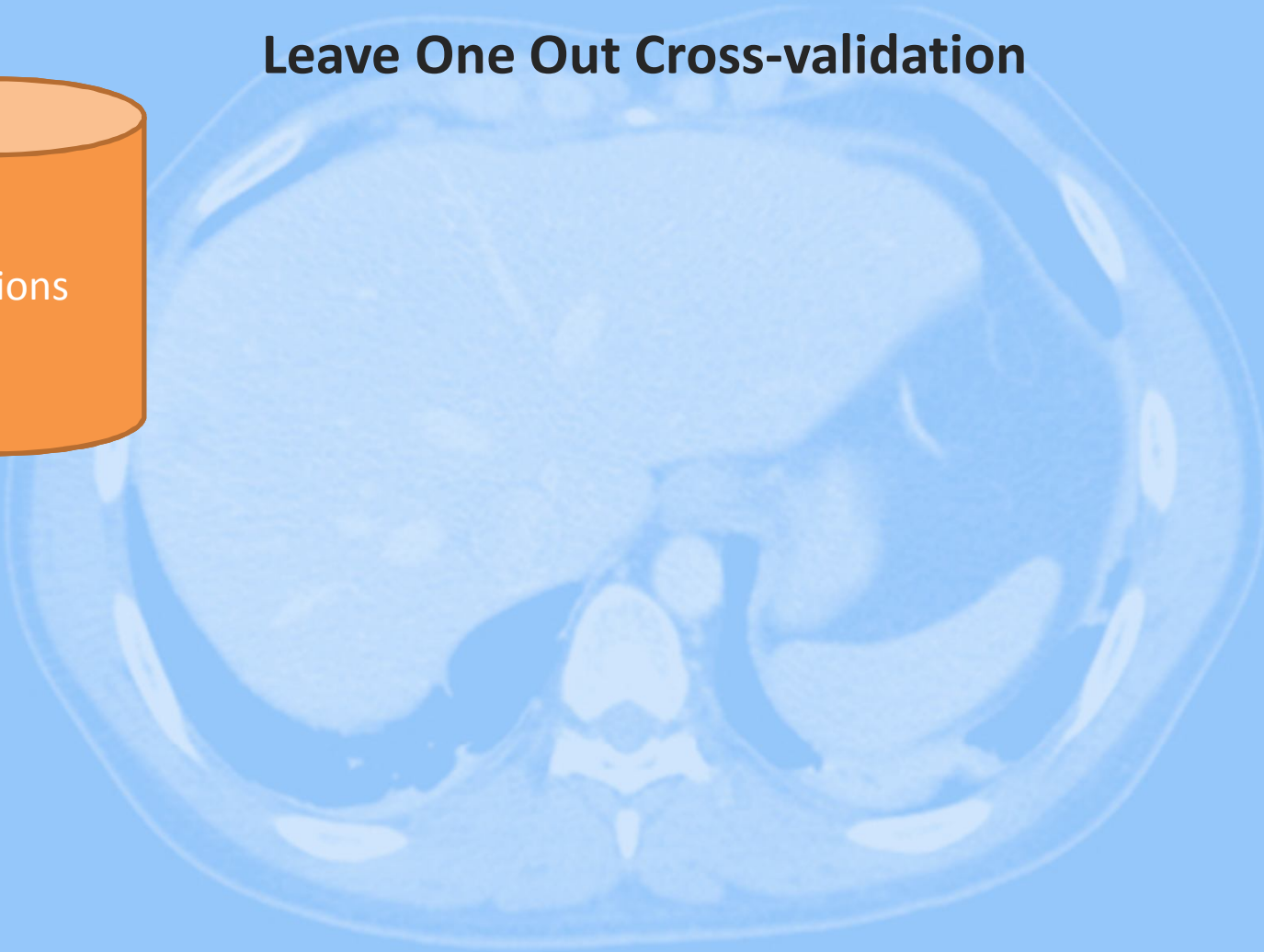
1 Platt J., *Fast Training of Support Vector Machines Using Sequential Minimal Optimization*, Advances in Kernel Methods - Support Vector Learning, MIT Press 2007

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.

Method

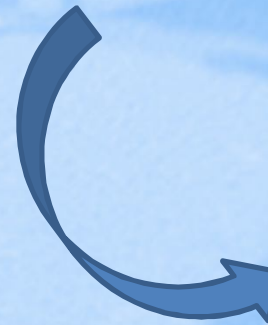
Classification evaluation

Leave One Out Cross-validation



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

Classification evaluation

Leave One Out Cross-validation



Leave One Out (LOO)

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

Exhaustive:
 n different partitions

Cross-validation

1. Split the database in learning and testing data
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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

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

i a given class

Precision & Recall 1/2

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- Measure of the ability to select instances of a certain class
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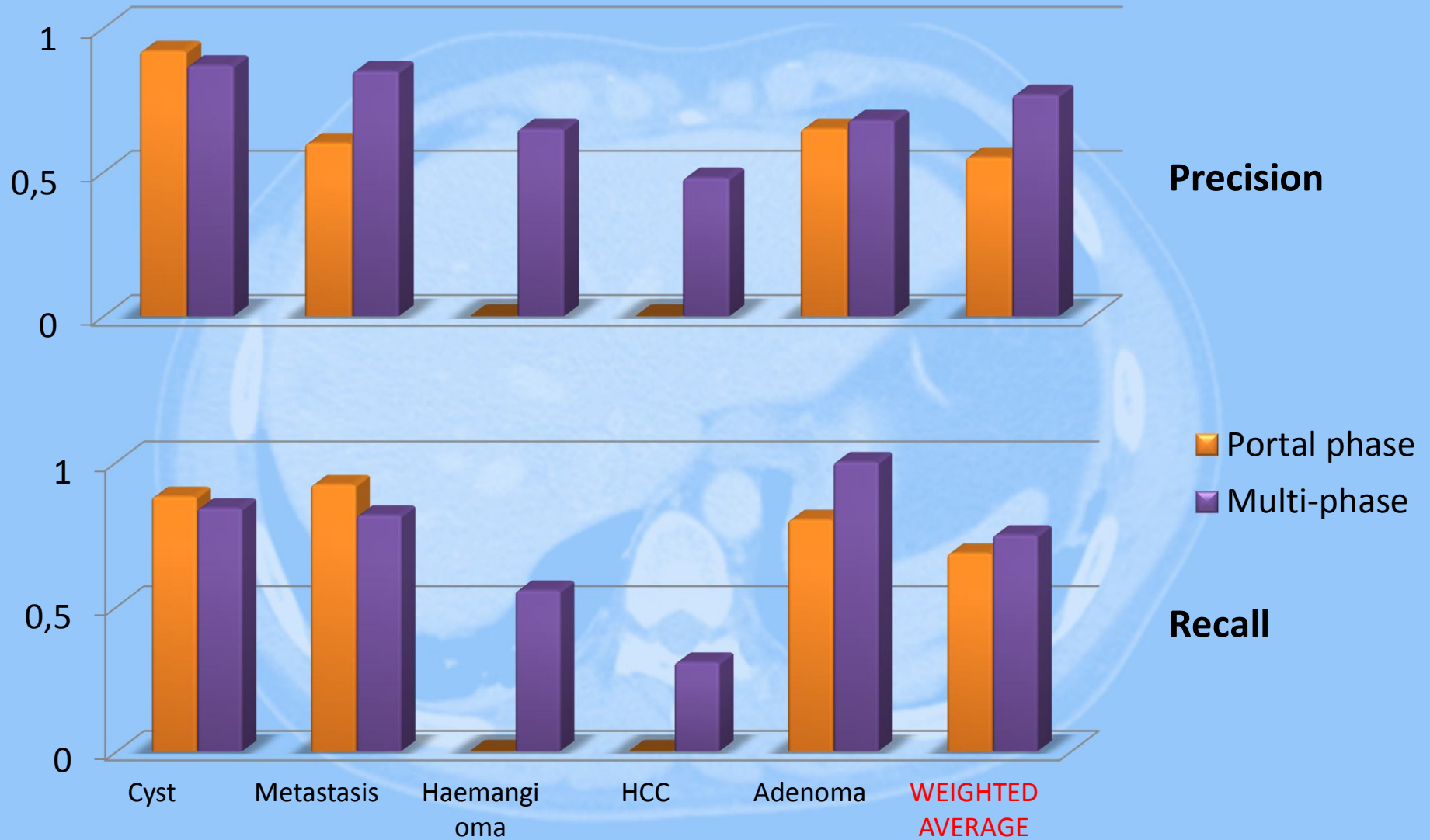
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Range [0 1] with 1.00 the best

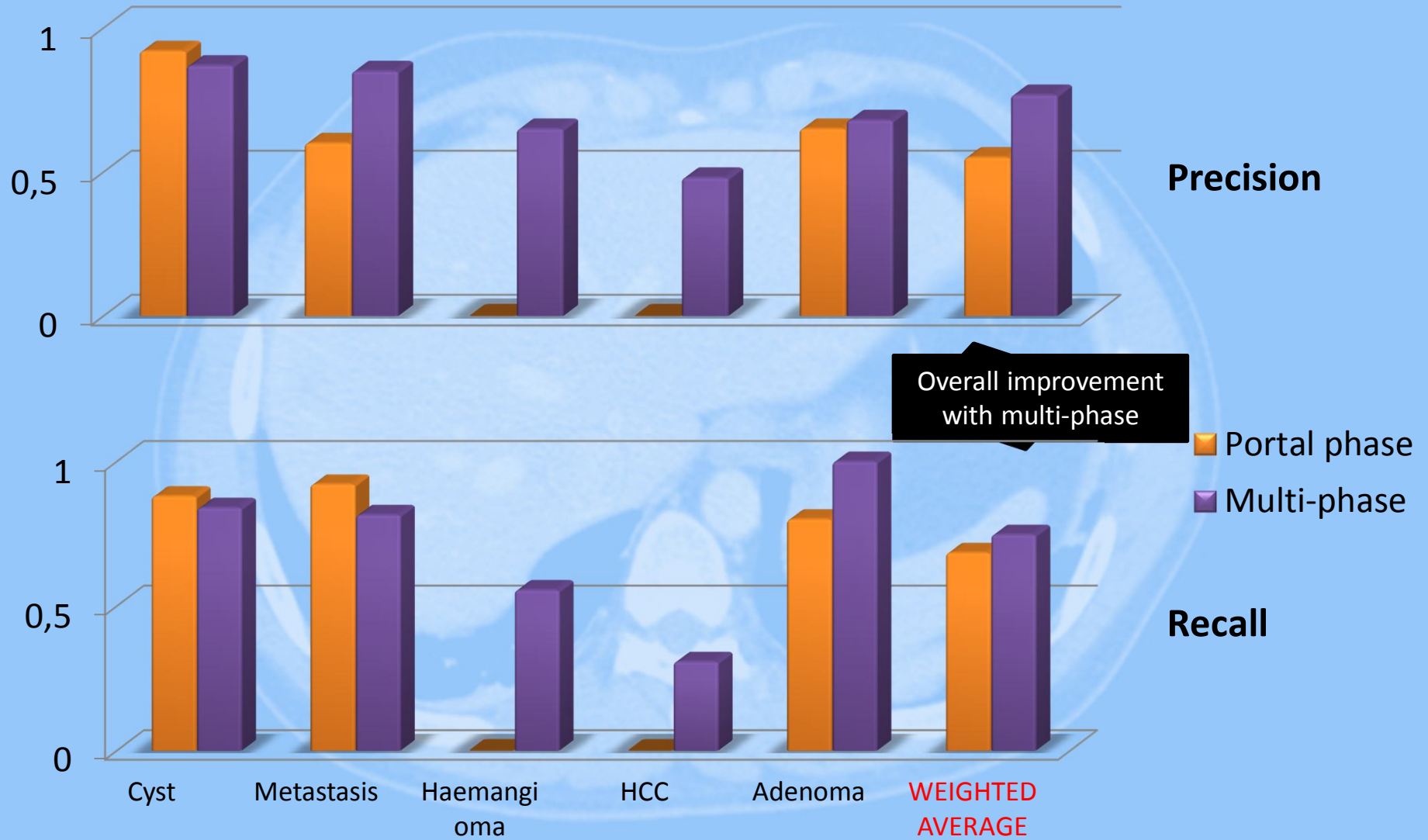
Results

Precision & Recall 2/2



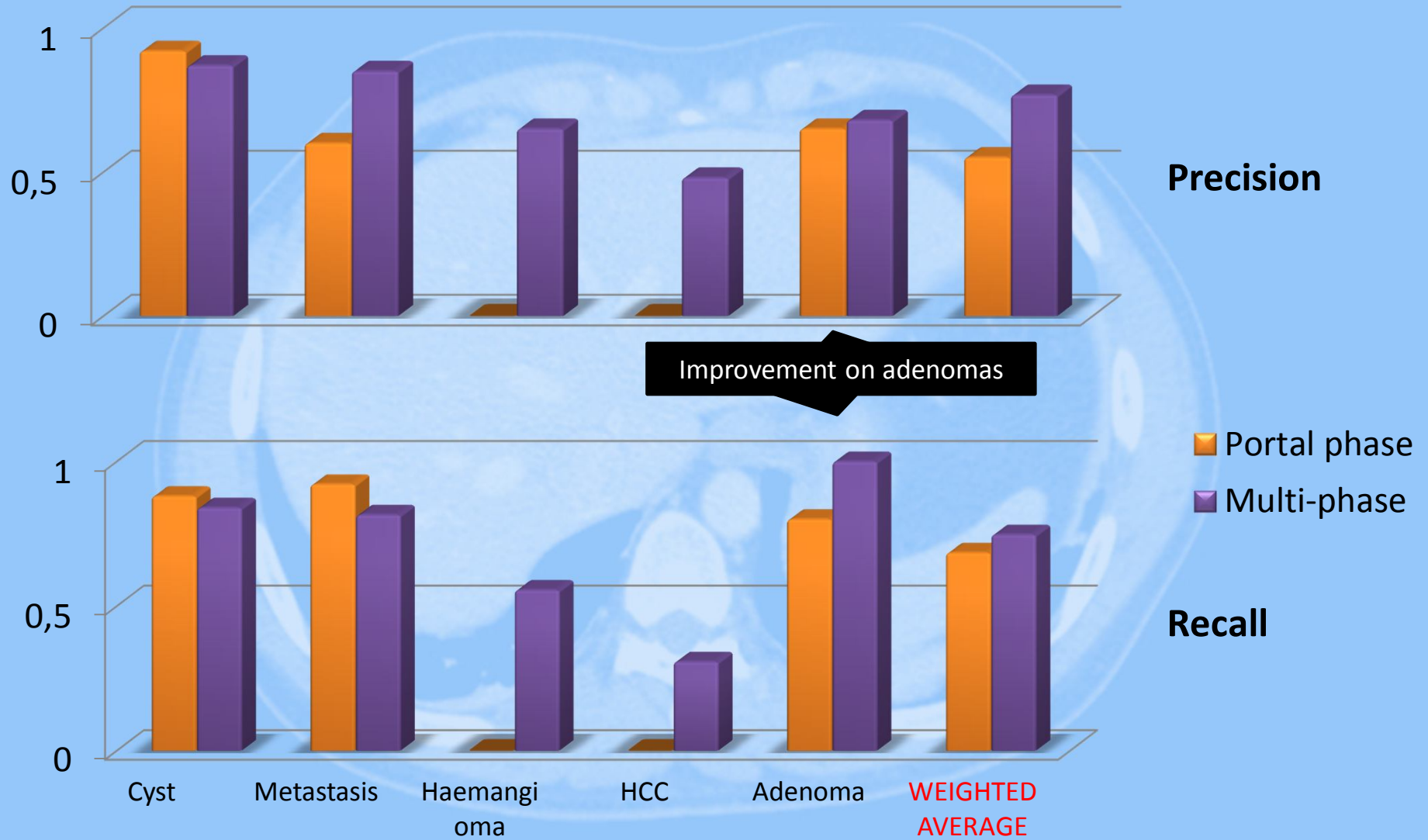
Results

Precision & Recall 2/2



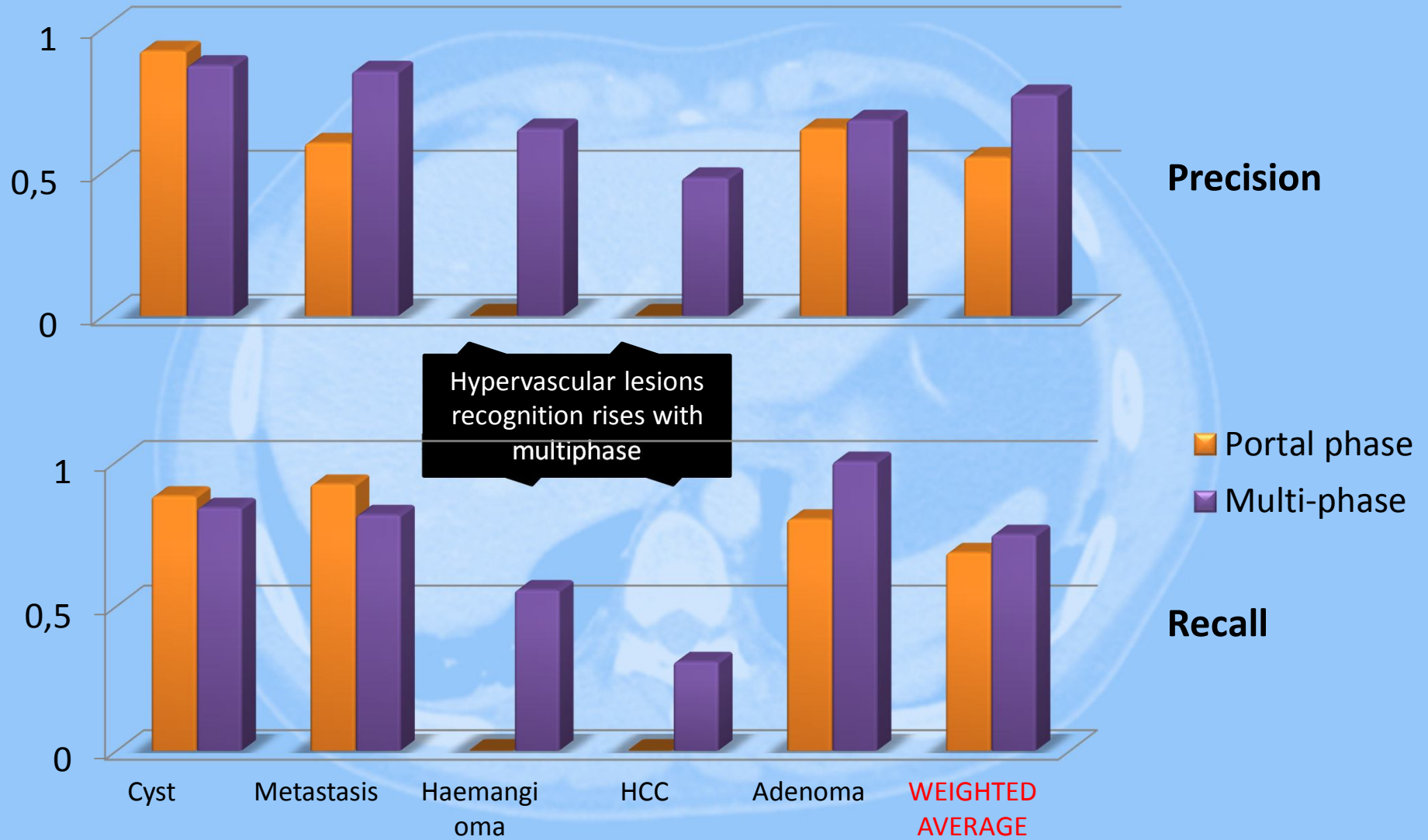
Results

Precision & Recall 2/2



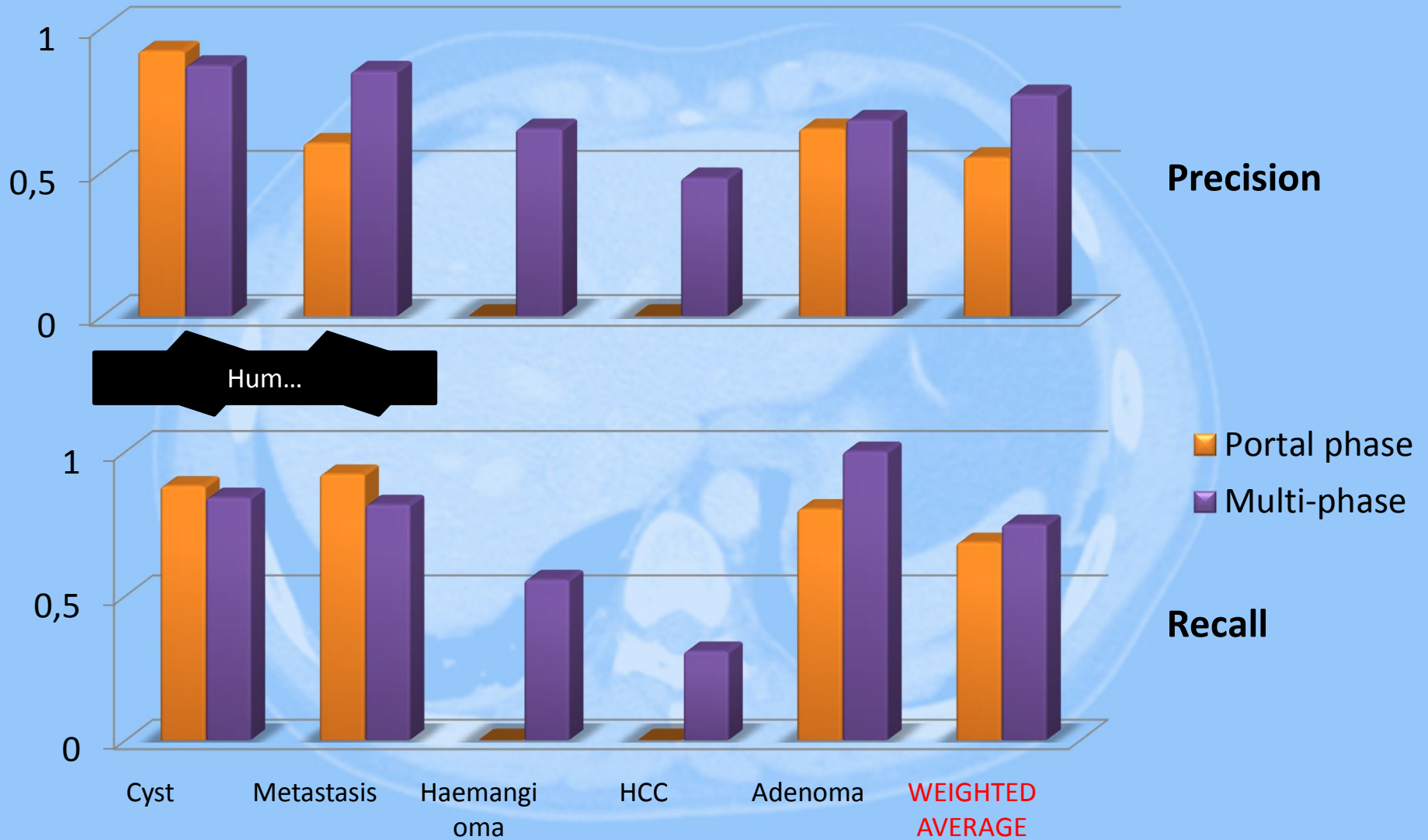
Results

Precision & Recall 2/2



Results

Precision & Recall 2/2



Results

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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We find the same information as from precision & recall

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

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Metastasis problem:

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

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

But the results are spread out on the other axis.

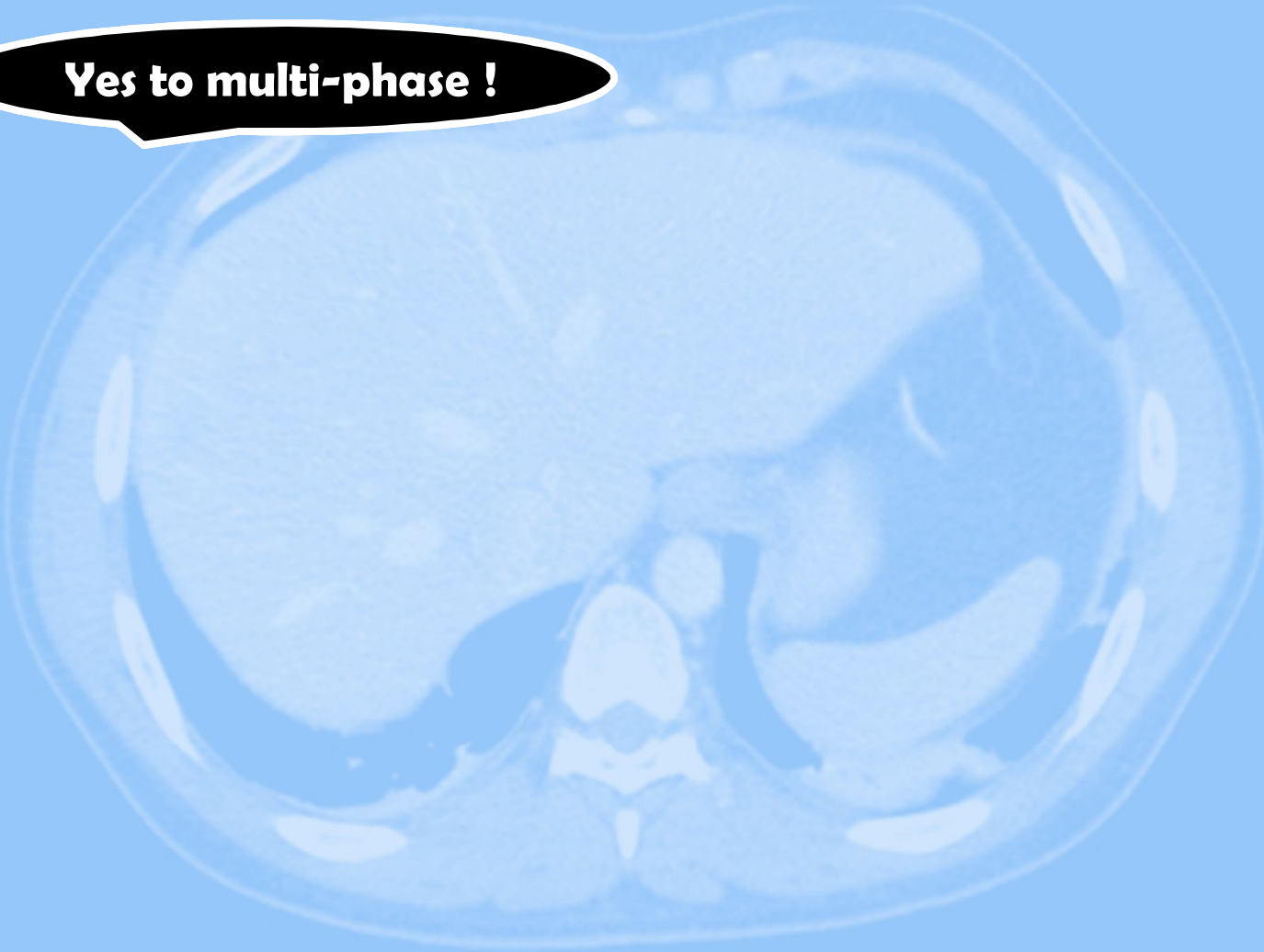
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Results

Discussion

Yes to multi-phase !

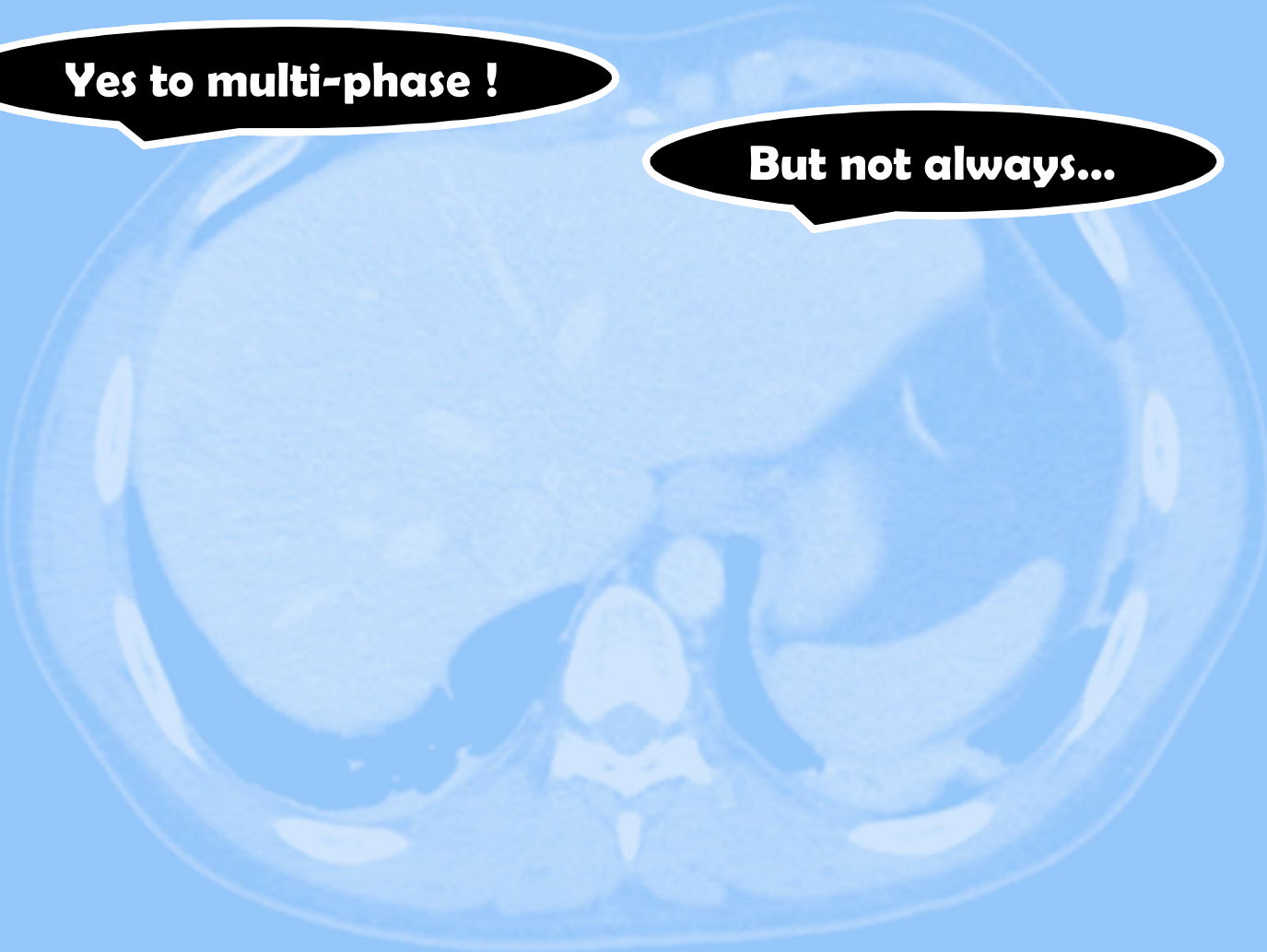


Results

Discussion

Yes to multi-phase !

But not always...



Results

Discussion

Yes to multi-phase !

But not always...

1. Two-step classification ?

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

Yes to multi-phase !

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1. Two-step classification ?

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

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

Layout

- Introduction
- Data
- Method
- Results
- Comparison
 - Overview
 - Data
 - Method
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How do we perform compared to others ?



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

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1 J. Ye, Y. Sun, S. Wang, L. Gu, L. Qian and J. Xu, *Multi-phase CT Image Based Hepatic Lesion Diagnosis by SVM*, 2nd IEEE International Conference on Biomedical engineering and Informatics, p.1-5, 2009.

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

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

Expertise

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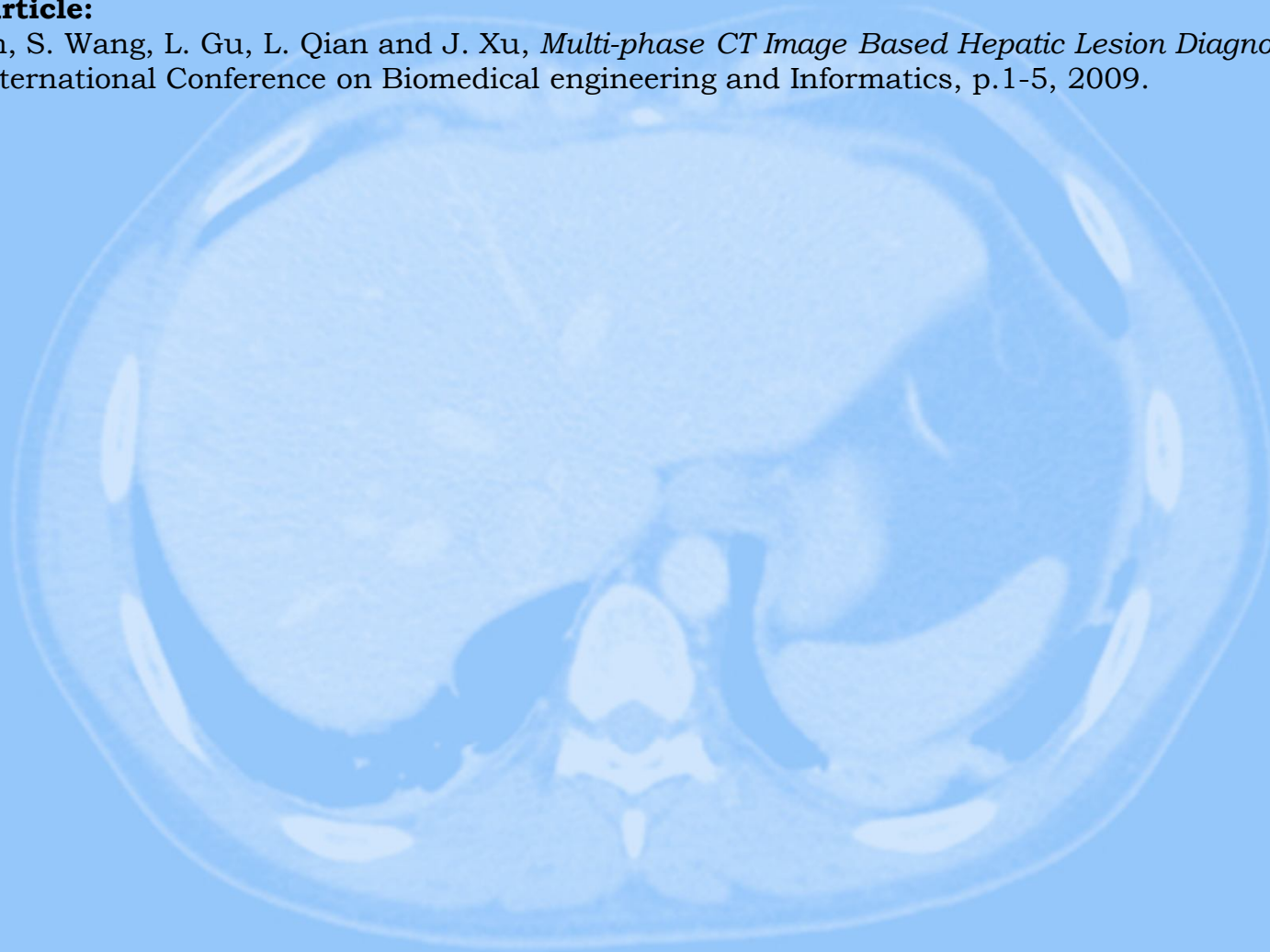
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	Time	Temporal features	-	-
Classifier			SVM	
Classification		3 binomial sequential classifications on each phase: -Healthy vs pathological -If pathological: cyst vs non-cyst -If non-cyst: HCC vs haemangioma	Distinguish the 3 classes on multi-phase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

Comparison

Experiment

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49 lesions
from 41
patients

Database

Healthy liver	cyst	haemangioma	HCC
5	25	9	10

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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 kontras.	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
Late	0.89	0.97	0.89	0.86	0.98	0.63
All	-	-	-	0.98	0.95	0.74

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Comparison

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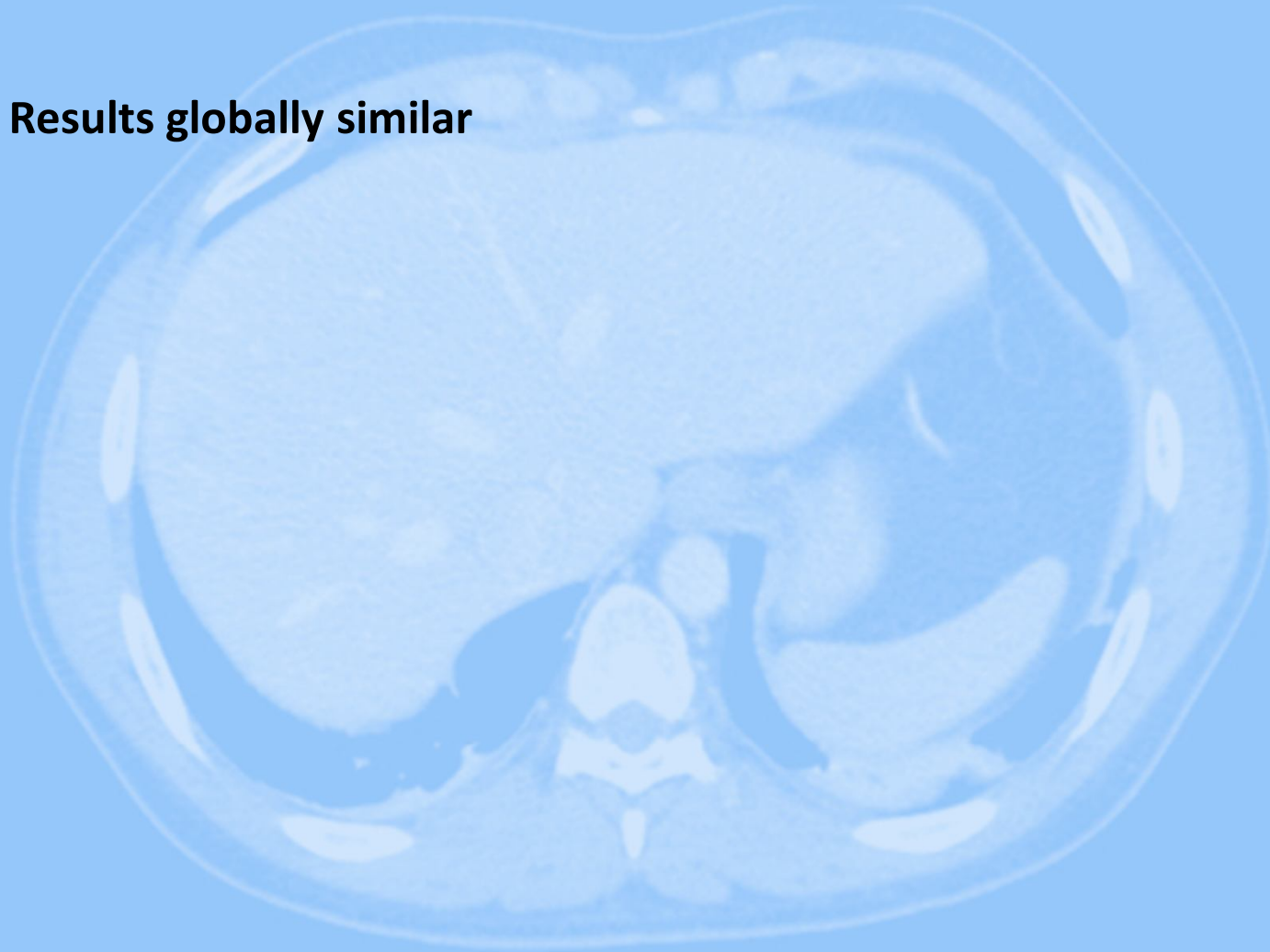
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Comparison

Discussion

1. Results globally similar



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2. Main difference between our systems: the ROI

Ye et. al ROI:

Manual 16*16 pixels square
representative of the lesion

Our ROI:

Ellipse as close as possible to the lesion
But may be heterogeneous
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3. Phase by phase analysis is necessary

Layout

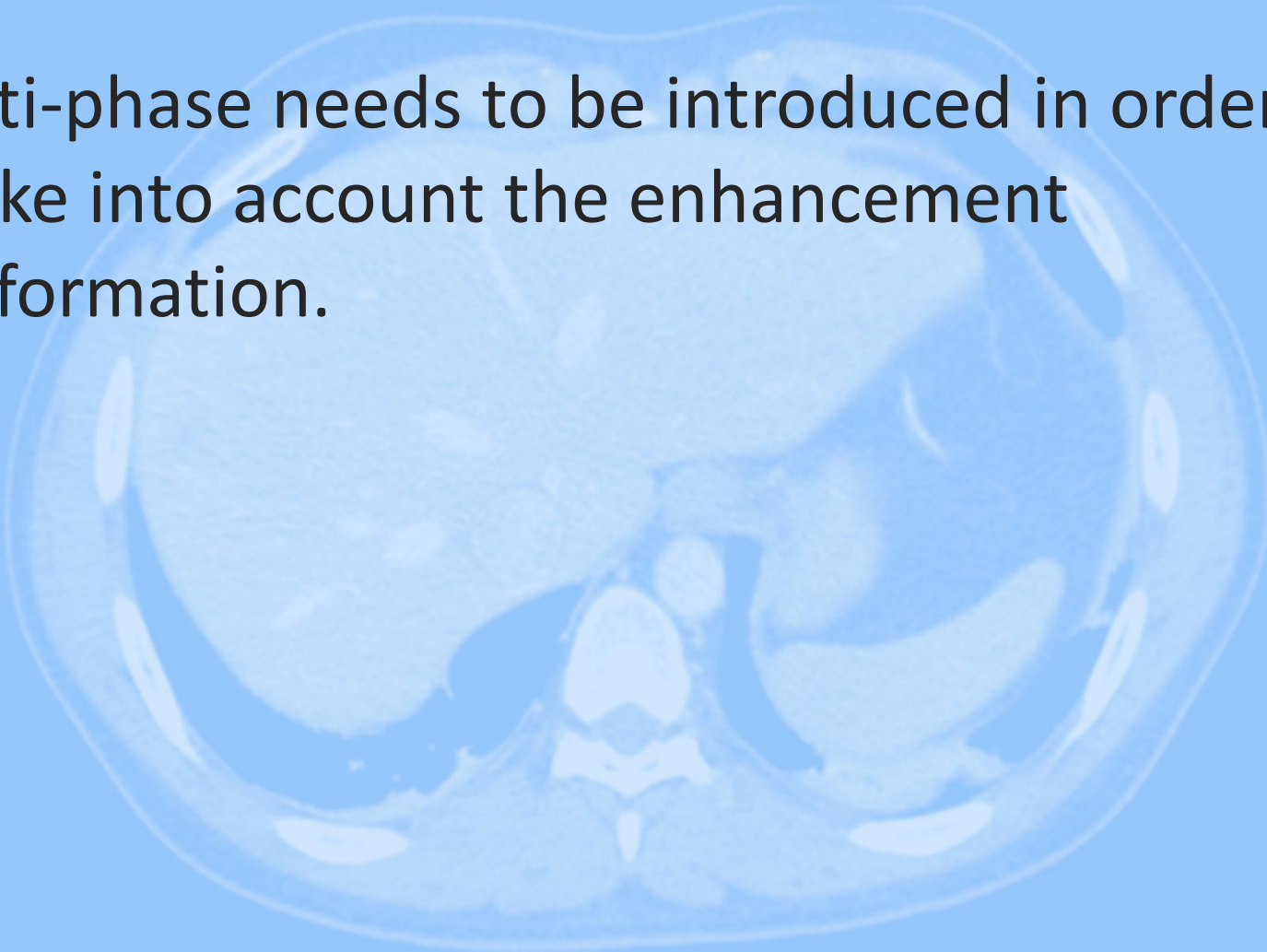
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Conclusion

Multi-phase

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



Conclusion

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.

Conclusion

Data

Database size should be increased
in order to validate the results



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

Conclusion

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



The screenshot displays the OsiriX DICOM viewer interface. On the left, a 'Local Database' window shows a list of 107 studies. The main area features a grid of image thumbnails for various series. Two large image viewing windows are open, showing axial CT scans of a head. The top window displays a zoomed-in view of a specific slice, while the bottom window shows a wider view of the same slice. Both windows include technical details such as image size, view size, window level (WL), and window width (WW).

Patient name	Report	Lock	Patient ID	Age	Accession Number	Study Description	Modality	ID	Date Acquired
M10011 (4 series)			M10011		10807901	Study	CT	M10011	09/04/10 1
M10012 (4 series)			M10012		11714147	Study	CT	M10012	26/09/10 1
M10013 (2 series)			M10013		11428283	Study	CT	M10013	27/07/10 1
M10014 (3 series)			M10014		09445863	Study	CT	M10014	04/08/09 1
M10015 (4 series)			M10015		06144831	Study	CT	M10015	06/11/07 2
M10016 (4 series)			M10016		11846169	Study	CT	M10016	03/11/10 1
M10017 (2 series)			M10017		10447107	Study	CT	M10017	29/01/10 2
M10018 (4 series)			M10018		11846169	Study	CT	M10018	03/11/10 1
M10019 (4 series)			M10019		12003478	Study	CT	M10019	18/11/10 1
M10020 (4 series)			M10020		13634482	Study	CT	M10020	13/09/11 1
M10021 (2 series)			M10021		10447107	Study	CT	M10021	29/01/10 2
M10022 (4 series)			M10022		13620928	Study	CT	M10022	13/09/11 1
M10023 (4 series)			M10023		12927128	Study	CT	M10023	29/04/11 1
M10024 (4 series)			M10024		13694767	Study	CT	M10024	22/09/11 1
M10025 (2 series)			M10025		10447107	Study	CT	M10025	29/01/10 2
M10026 (4 series)			M10026		12637223	Study	CT	M10026	15/03/11 1
M10027 (2 series)			M10027		10447107	Study	CT	M10027	29/01/10 2
M10028 (3 series)			M10028		11515705	Study	CT	M10028	18/08/10 1
M10029 (4 series)			M10029		13443859	Study	CT	M10029	02/08/11 1
M10030 (4 series)			M10030		13620928	Study	CT	M10030	13/09/11 1
M10031 (3 series)			M10031		11490218	Study	CT	M10031	11/08/10 1