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Leading Innovation >>>

Texture Analysis using Markov Random Fields

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supervised by

Keith Goatman

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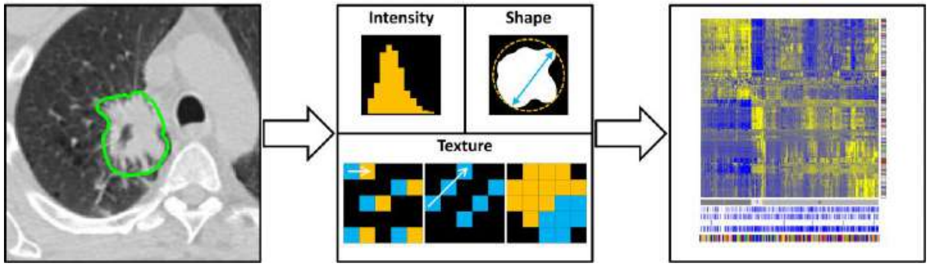
TOSHIBA MEDICAL SYSTEMS CORPORATION

Outline

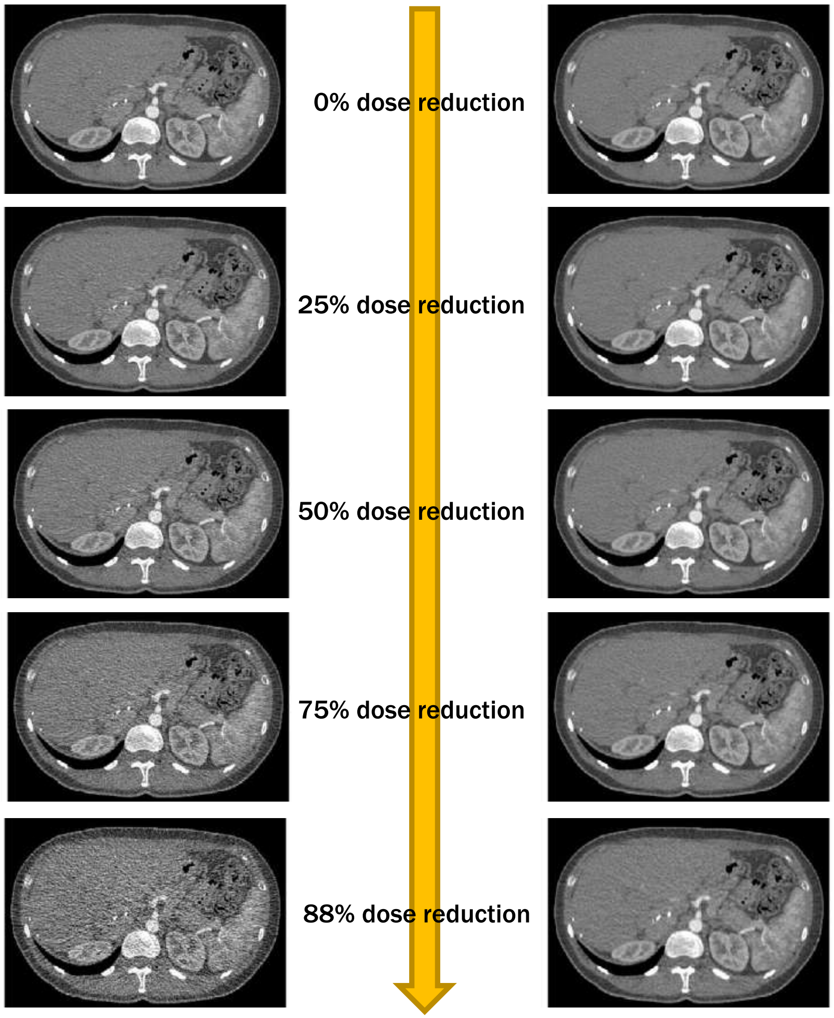
1. Motivation

Radiomics



Given an image and a region of interest, measure lots and lots of things in and about the ROI, e.g. volume, shape, texture [1]

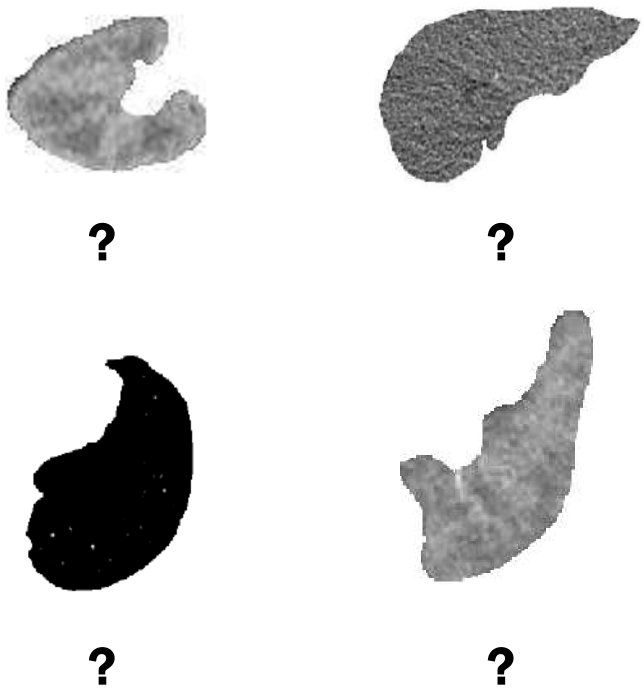
AIDR3D [2]



2. Aims

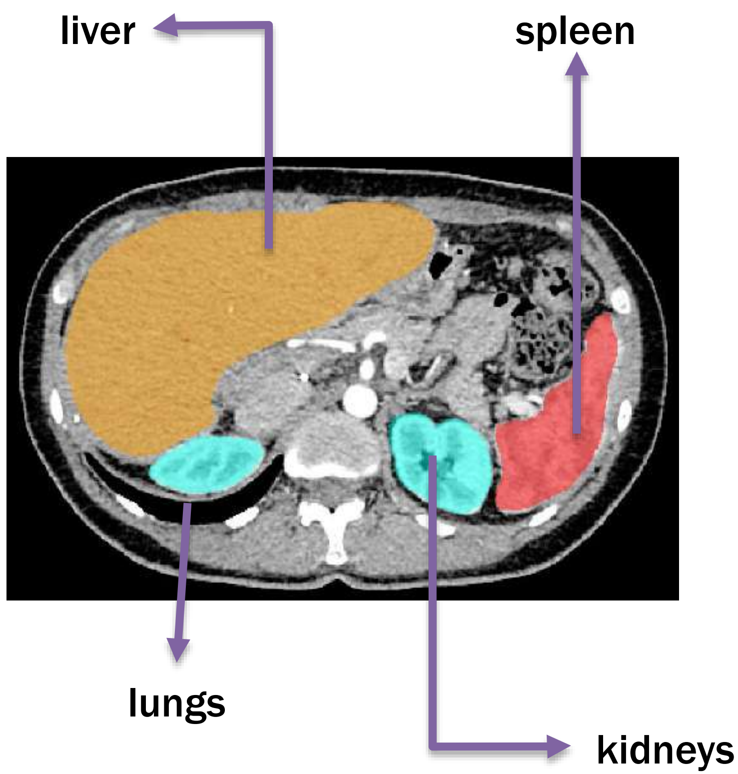
Classification

Classify 2D masks into different tissues:
kidneys, liver, lungs and spleen



Region classification

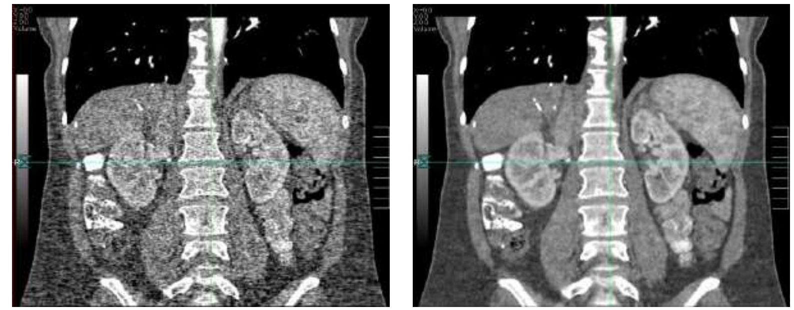
Segmentation



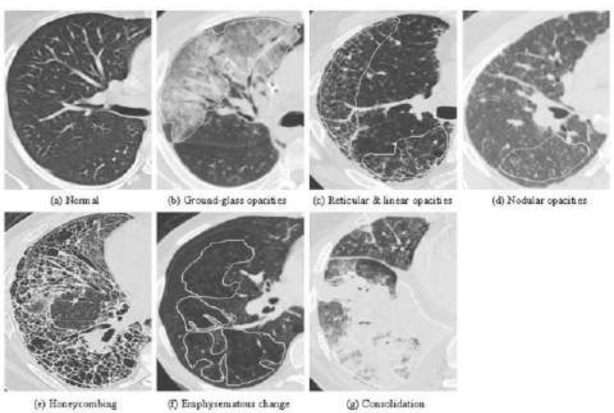
Pixel classification

3. Problem

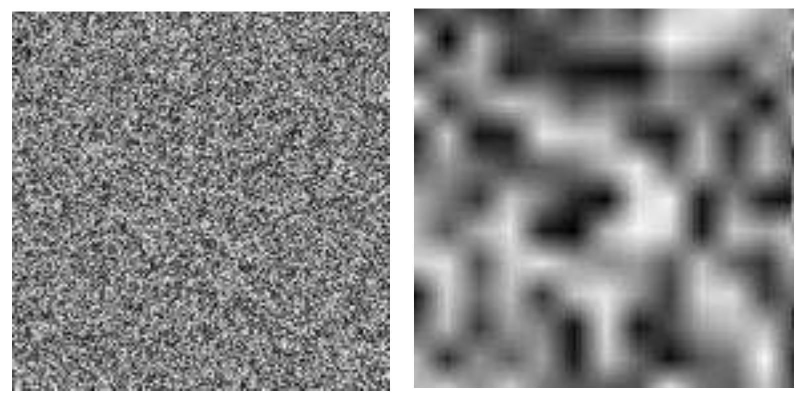
Wide Dynamic Range



Noise

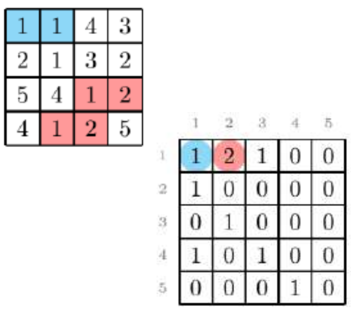


Texture Inhomogeneity [3]

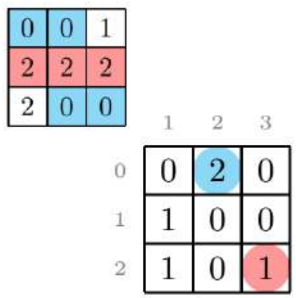


Scale

4. State of the Art

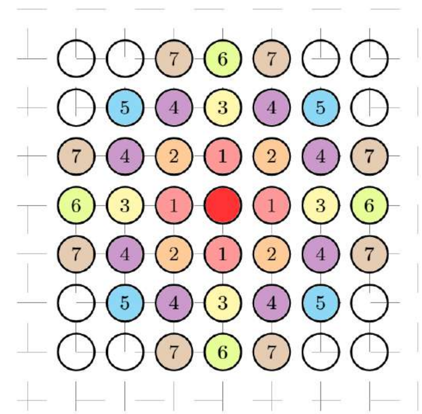


Gray-Level Co-ocurrence Matrix (GLCM)



Gray-Level Run-Length Matrix (GLRLM)

Baseline: Statistical Methods



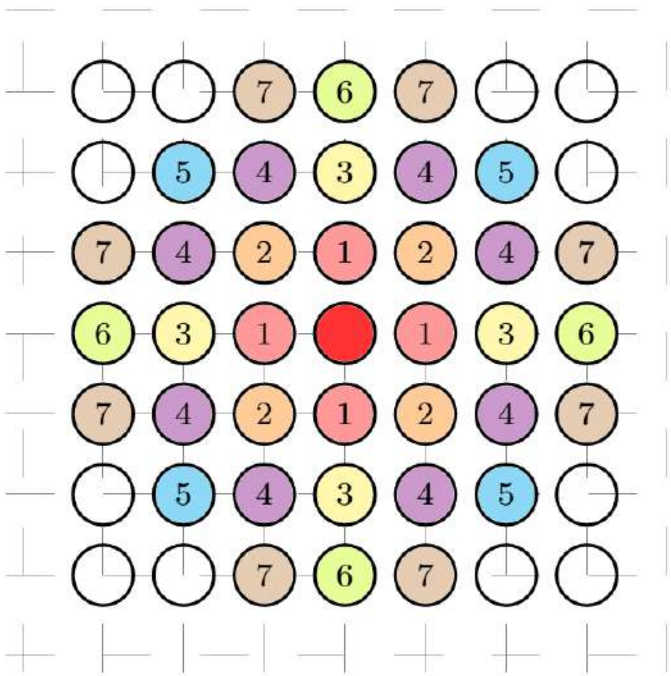
Markov Random Fields

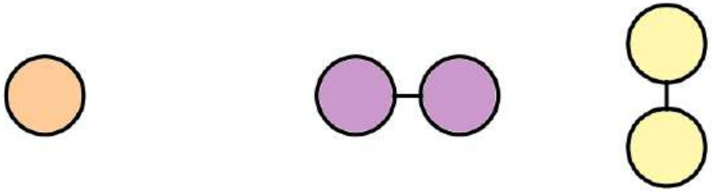
Model-based Methods

5.1 Parametric Markov Random Fields

MRF characterize mutual influences among pixels using conditional MRF distributions, that is to say, they derive the joint distribution from conditional distributions

$$p(I(x_c)|I(x), \forall x \neq x_c) = p(I(x_c)|I(x), x \in \mathcal{N}(x_c))$$





cliques

$$l* = \arg\max_{l} P(l|x) = \arg\min_{l} E(l;x)$$

5.2 Non-parametric Markov Random Fields

Varma and Zisserman [4] proposed a non-parametric Markov Random Field, based on a two dimensional histogram

Learning

Classification

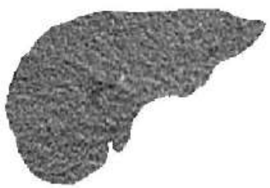
- High accuracies on challenging datasets
- The method relies on fewer prior assumptions, such as the form of the distribution.

6. Classification

Classification

Classify <u>2D masks</u> into different tissues: kidneys, liver, lungs and spleen

?



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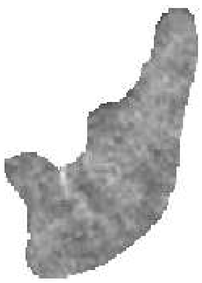
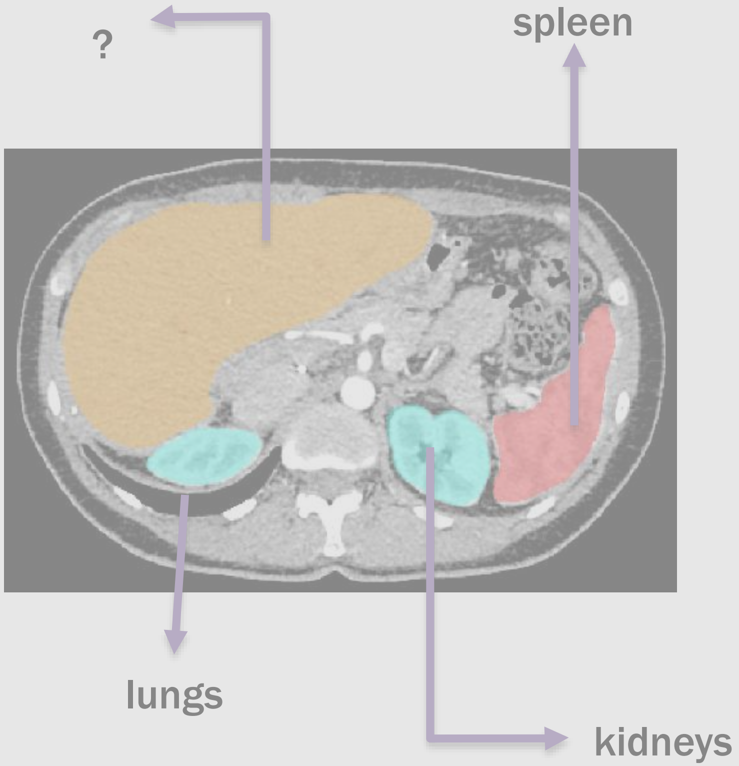
?



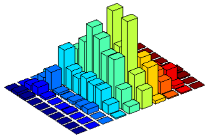
?

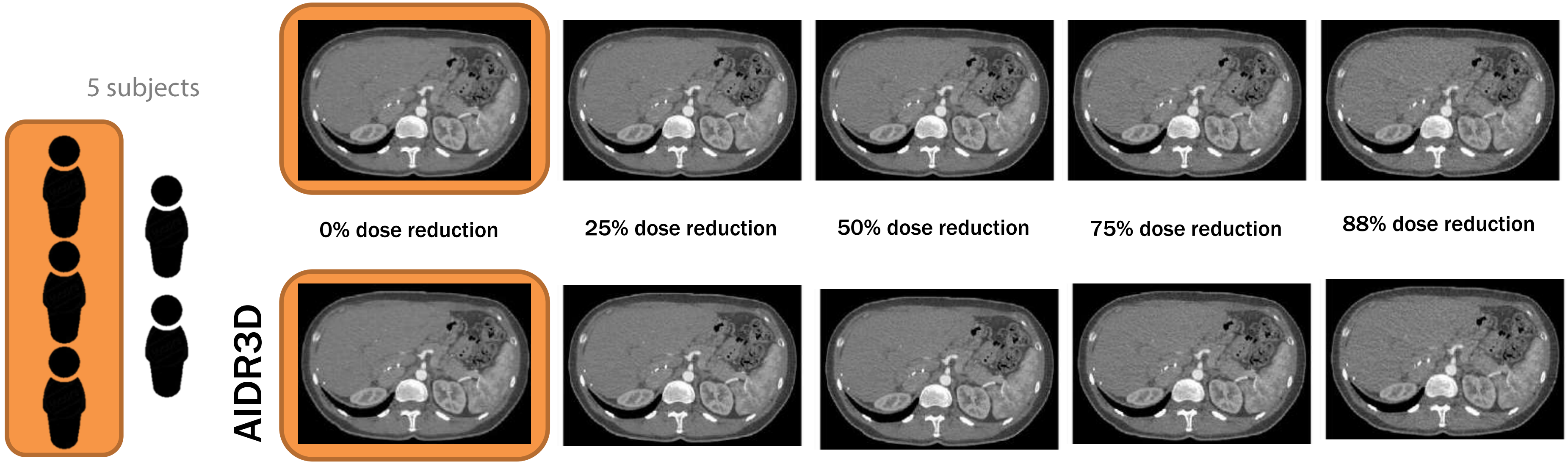
Segmentation



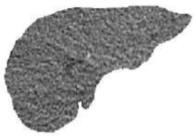
6.1 Classification: Methodology

Extract Textons → Aggregate Textons → K-means → Label Pixels

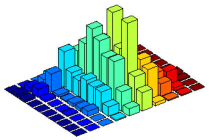




6.1 Classification: Methodology



Extract Textons → Aggregate Textons → K-means → Label Pixels →



1	4	8	
10	25	5	
1	7	3	

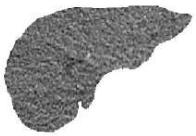
Intensity values

1	4	8	10	5	1	7	3

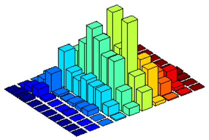
texton

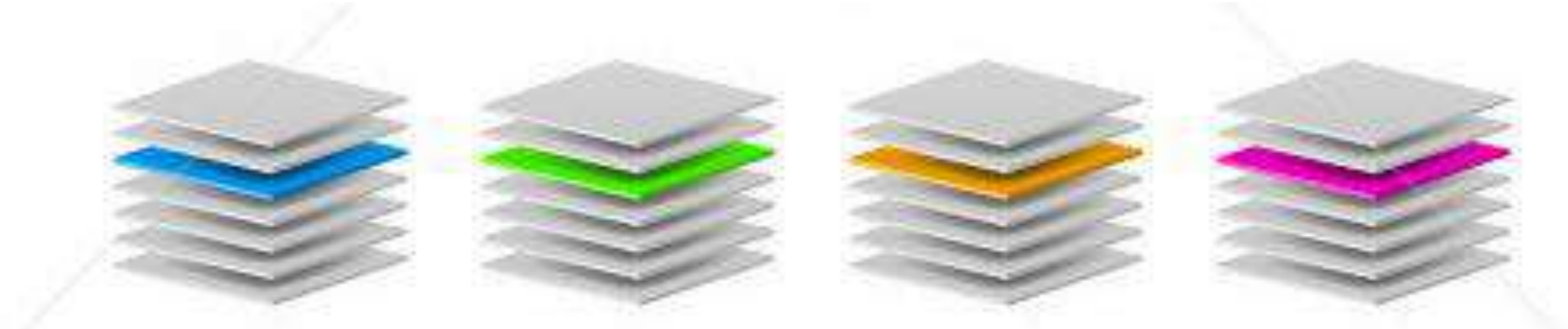
Parameters
Neighbourhood size

6.1 Classification: Methodology



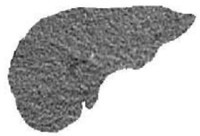
Extract Textons → Aggregate Textons → K-means → Label Pixels →



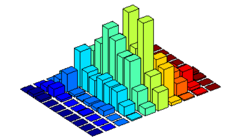


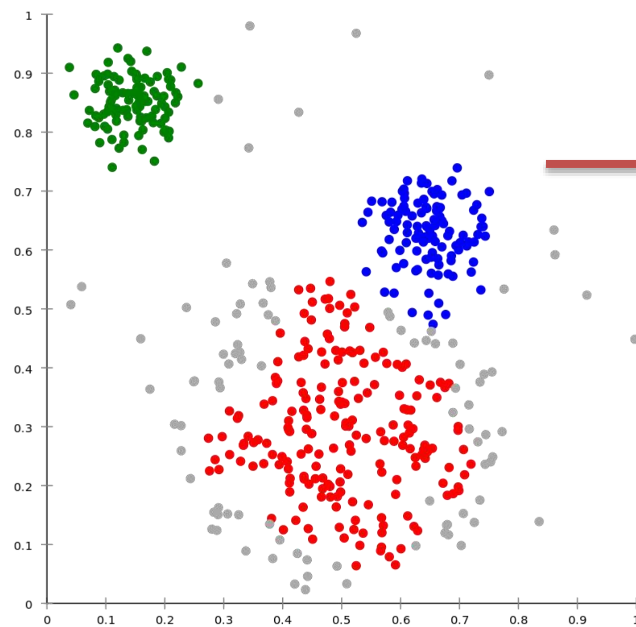
kidneys liver lungs spleen

6.1 Classification: Methodology

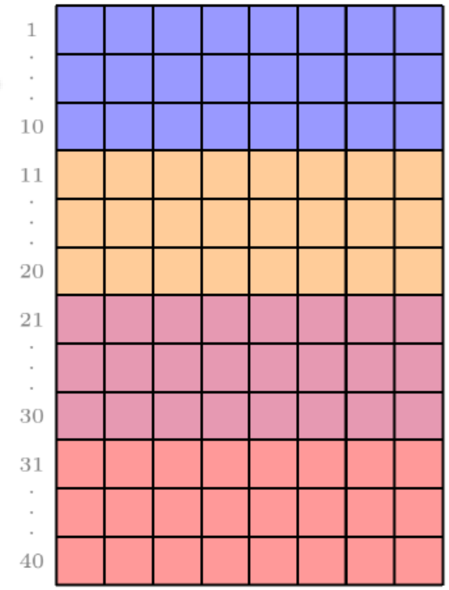


Extract Textons → Aggregate Textons → K-means → Label Pixels



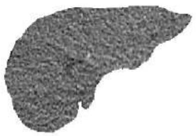


K-means per class

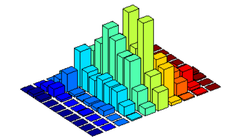


Parameters
Number of textons per class

6.1 Classification: Methodology



Extract Textons → Aggregate Textons → K-means → Label Pixels →



Intensity values

1	4	8	
10	25	5	
1	7	3	

texton

1	4	8	10	5	1	7	3

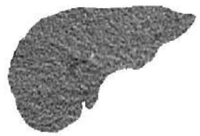
Textons dictionary

1	82	43	67	49	84	91	68	42
⋮	42	13	87	69	44	18	89	21
10	2	3	7	9	4	1	8	2
11	14	74	8	70	54	18	78	35
⋮	13	45	85	90	58	13	73	38
20	13	43	88	90	59	17	73	36
21	91	74	28	60	55	12	78	34
⋮	12	44	86	80	57	13	75	34
30	15	44	83	18	55	17	77	73
31	21	41	78	80	59	14	75	30
⋮	24	63	74	98	44	51	68	20
40	15	44	80	10	25	19	67	20

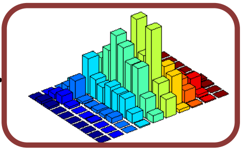
Labels

	10		

6.1 Classification: Methodology



→ Extract Textons → Aggregate Textons → K-means → Label Pixels →

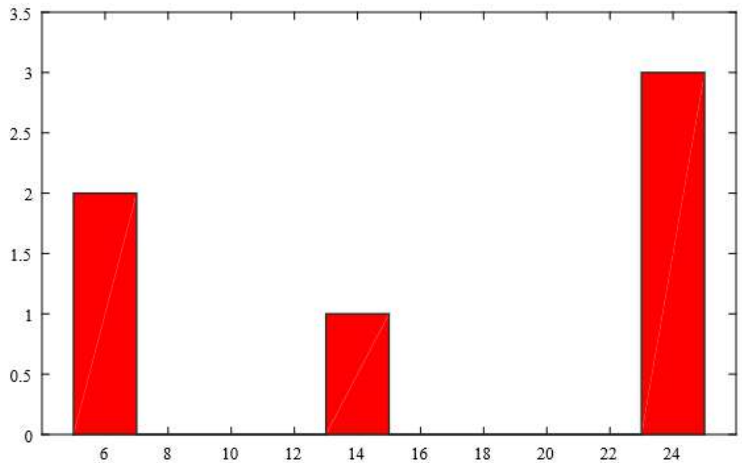


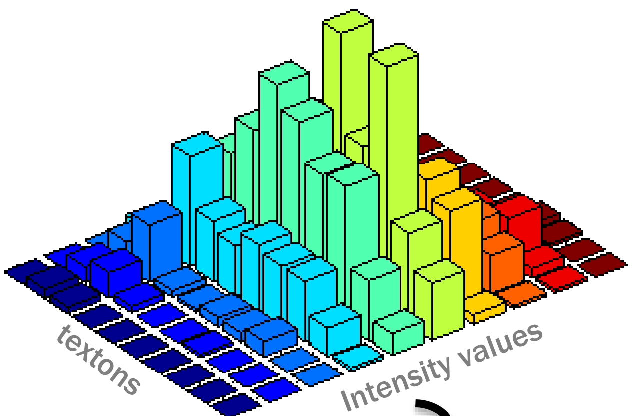
1	4	8	25
10	25	5	4
15	7	5	8
30	25	50	5

Intensity values

8	4	5	**10**
19	**10**	20	15
10	8	**10**	12
7	**10**	6	**10**

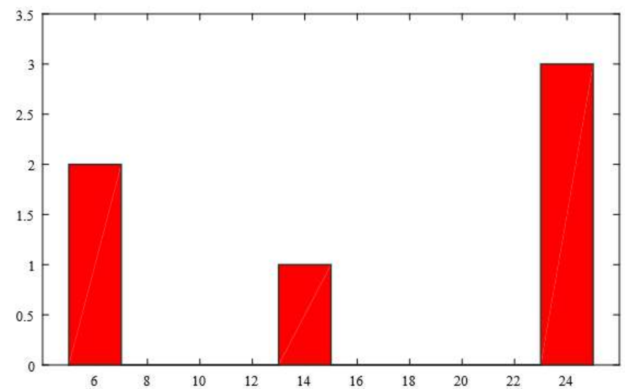
Labels



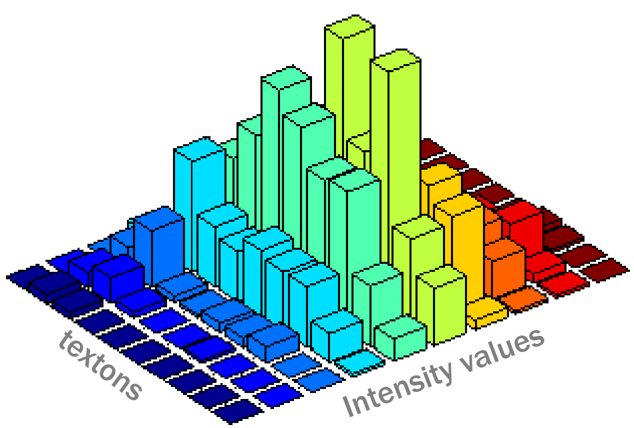


Parameter
Number of bins

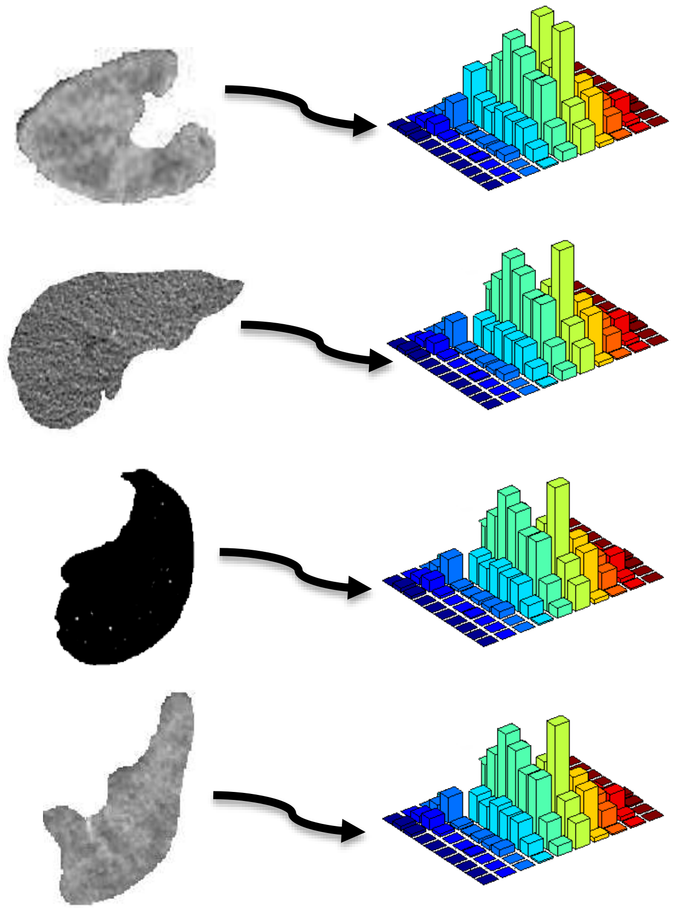
Varma and Zisserman proposed to model an MRF as a 2D histogram



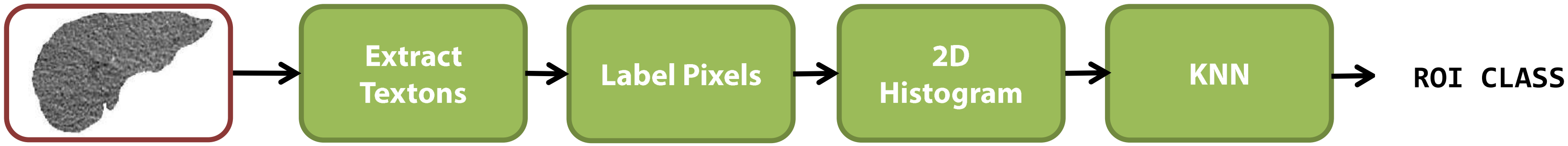
Probability density function

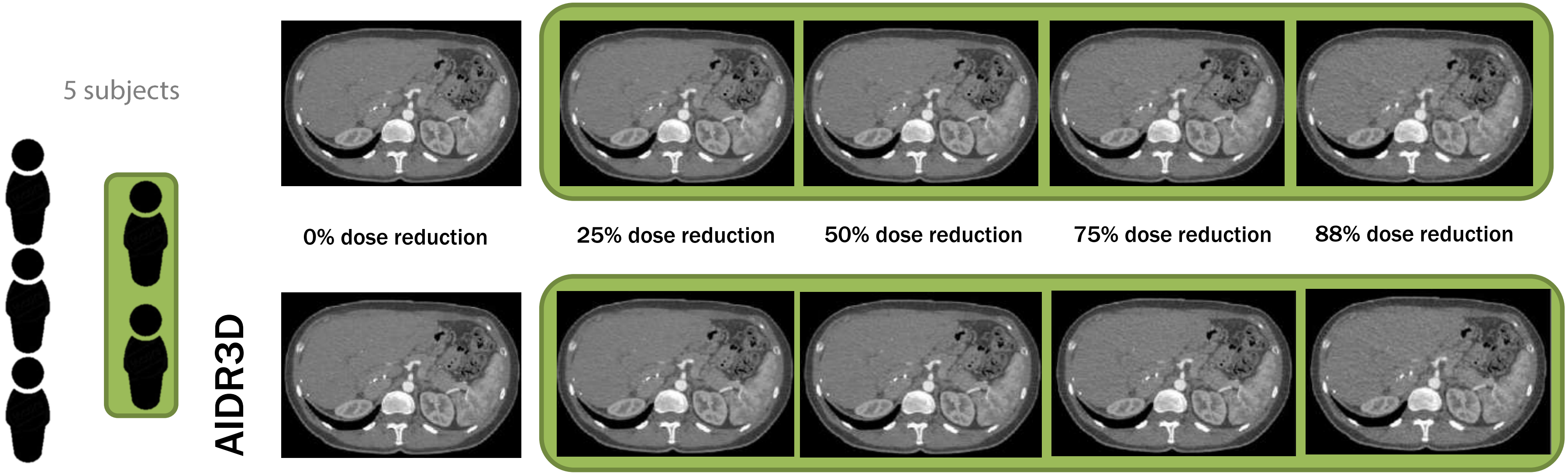


Joint pdf

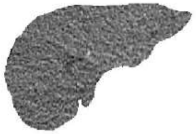


6.1 Classification: Methodology





6.1 Classification: Methodology



→ **Extract Textons** → **Label Pixels** → **2D Histogram** → **KNN** → ROI CLASS

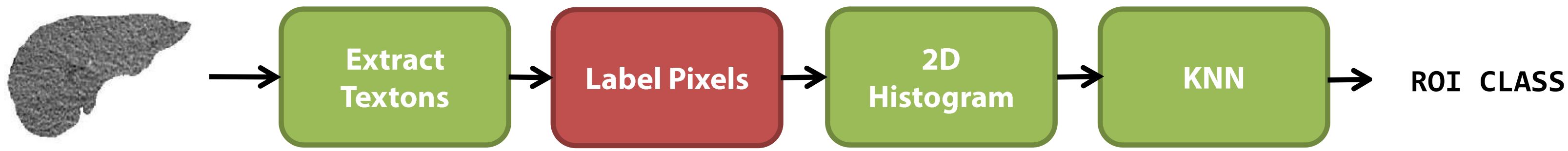
1	4	8	
10	25	5	
1	7	3	

Intensity values

1	4	8	10	5	1	7	3

texton

6.1 Classification: Methodology



texton

1	4	8	10	5	1	7	3

1	4	8	
10	25	5	
1	7	3	

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1	82	43	67	49	84	91	68	42
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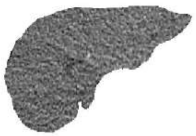
⋮	12	44	86	80	57	13	75	34
30	15	44	83	18	55	17	77	73
31	21	41	78	80	59	14	75	30
⋮	24	63	74	98	44	51	68	20
40	15	44	80	10	25	19	67	20

Textons dictionary

	10		

Labels

6.1 Classification: Methodology



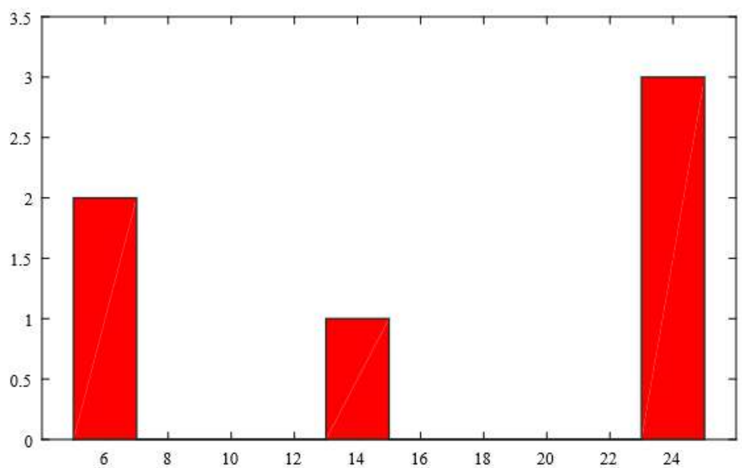
→ Extract Textons → Label Pixels → 2D Histogram → KNN → ROI CLASS

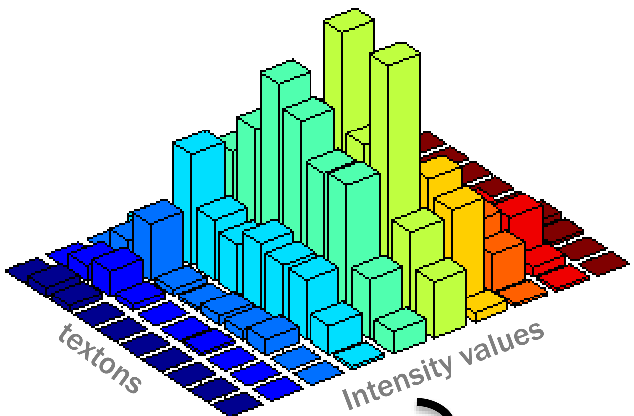
1	4	8	25
10	25	5	4
15	7	5	8
30	25	50	5

Intensity values

8	4	5	**10**
19	**10**	20	15
10	8	**10**	12
7	**10**	6	**10**

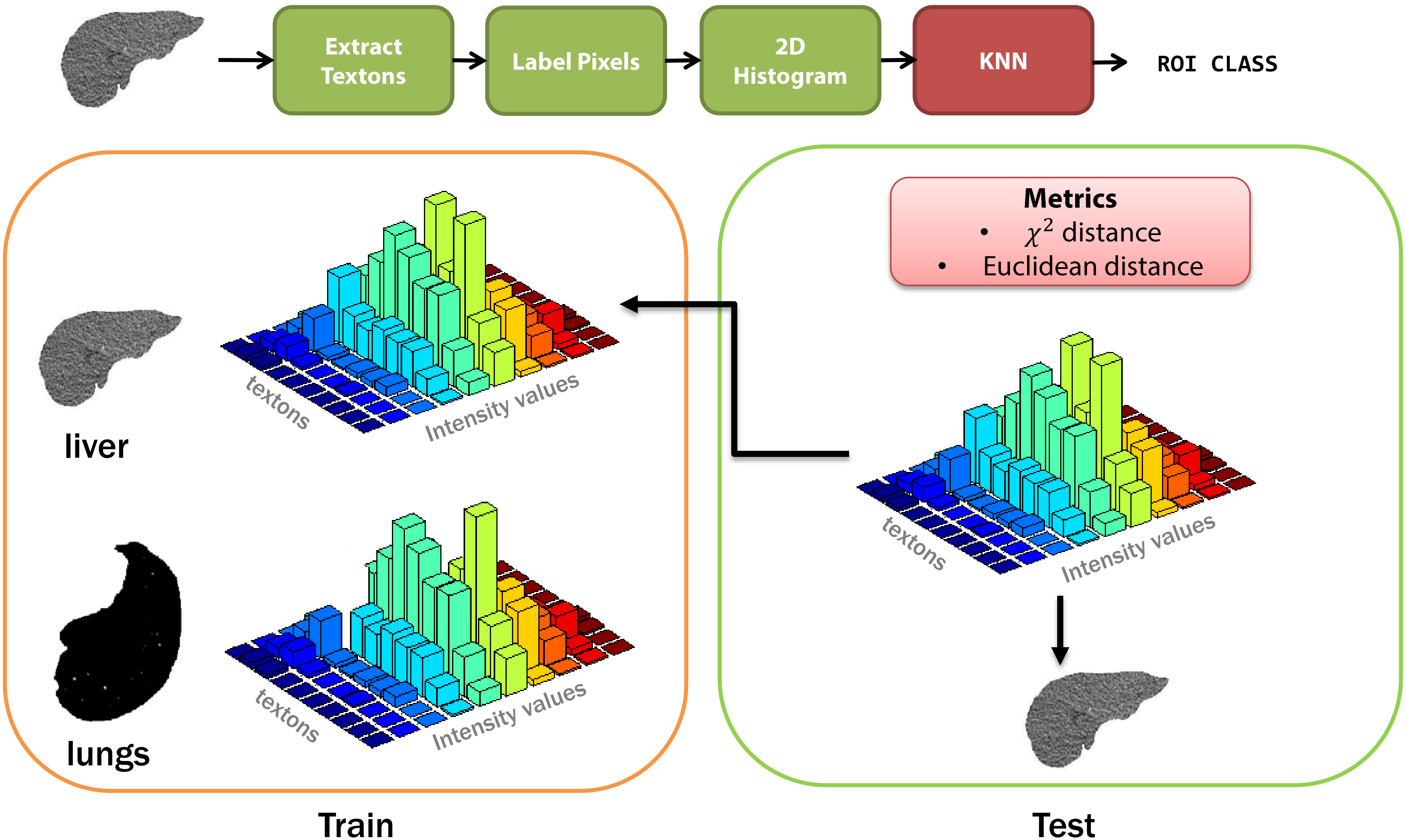
Labels



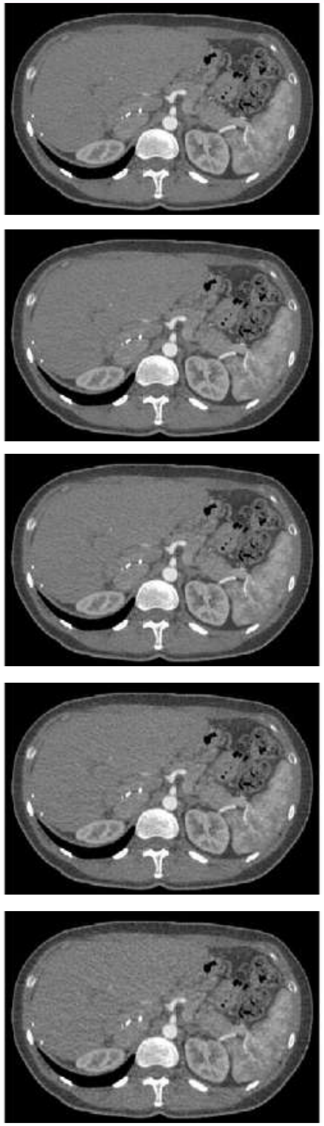


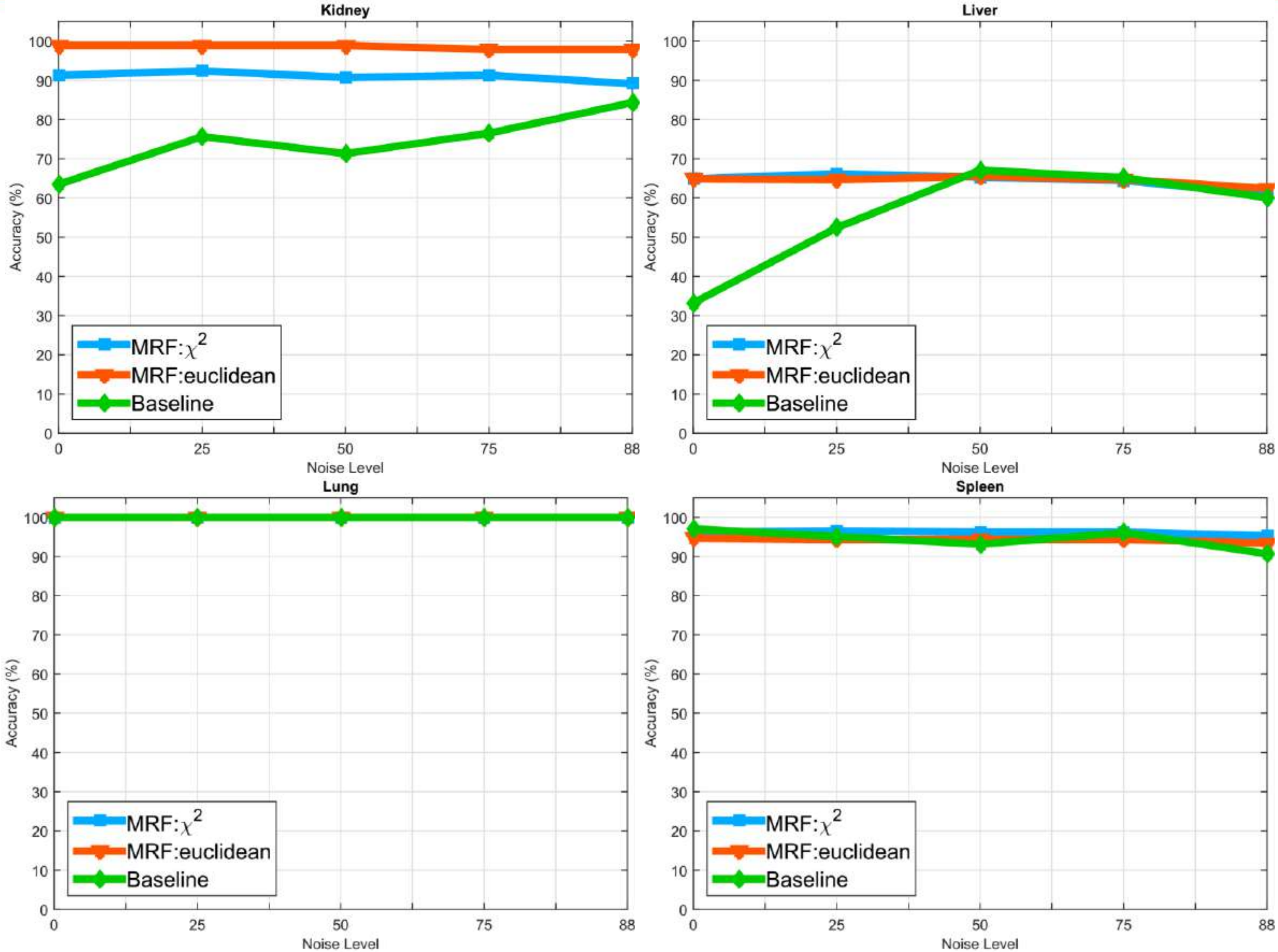
Parameter
Number of bins

6.1 Classification: Methodology



6.2 Classification: Results





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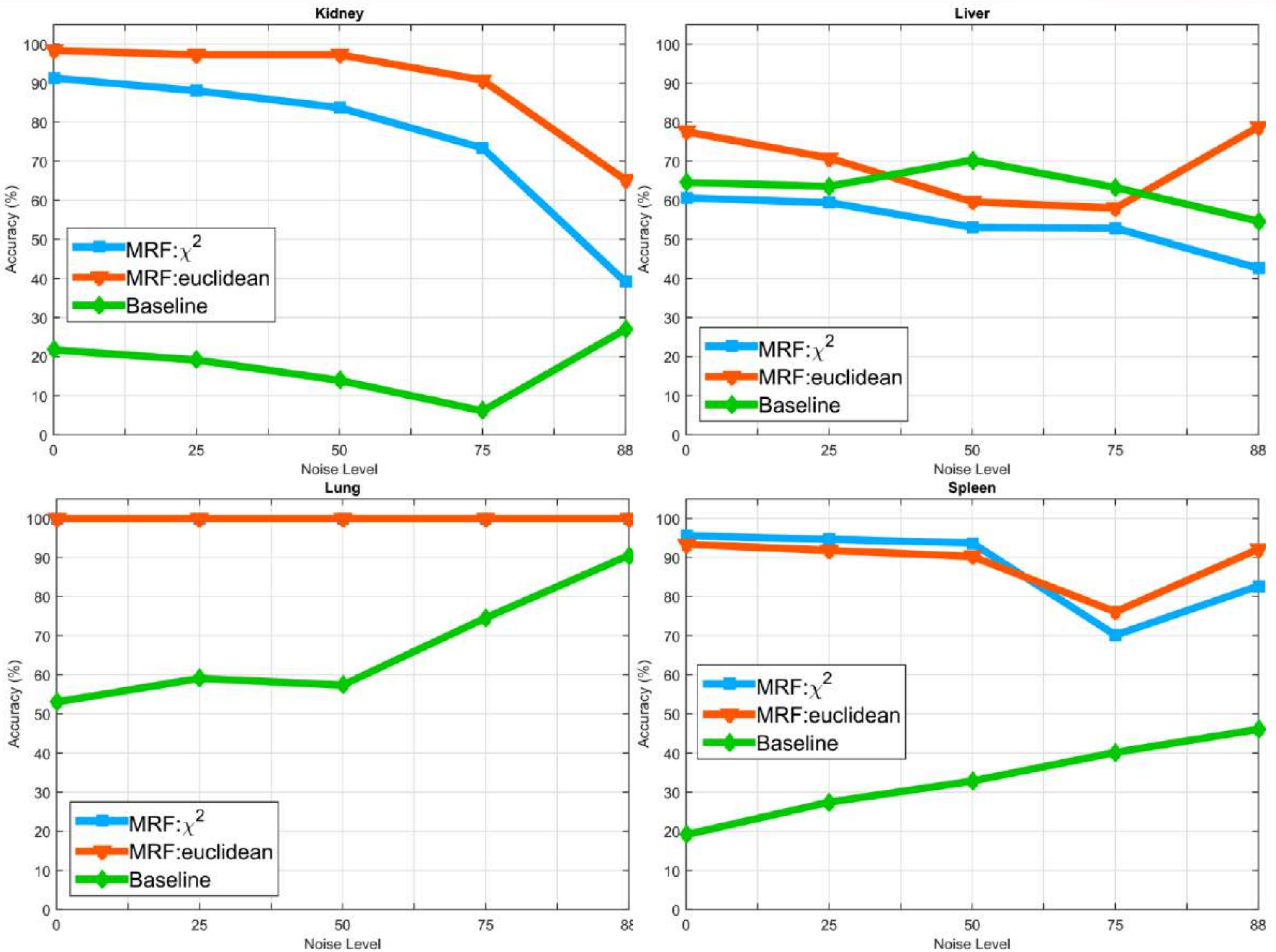
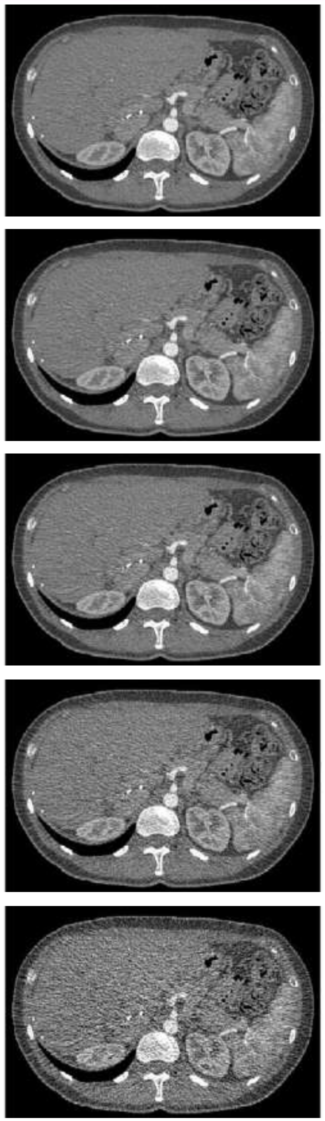




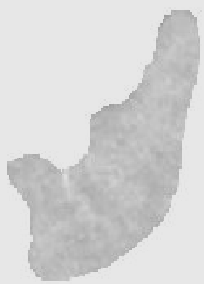
Classification

Classify 2D masks into different tissues:
kidneys, liver, lungs and spleen

?

?

?



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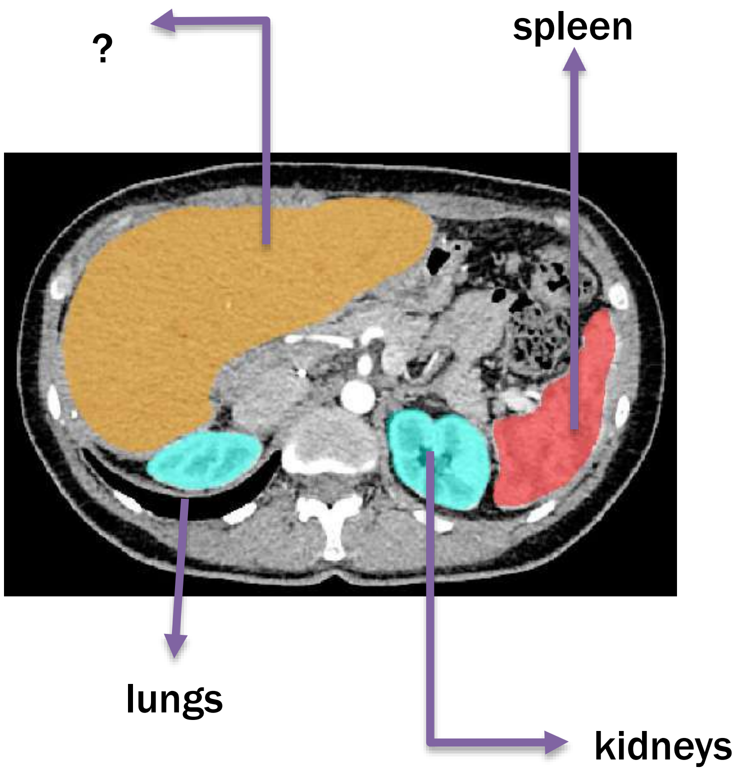
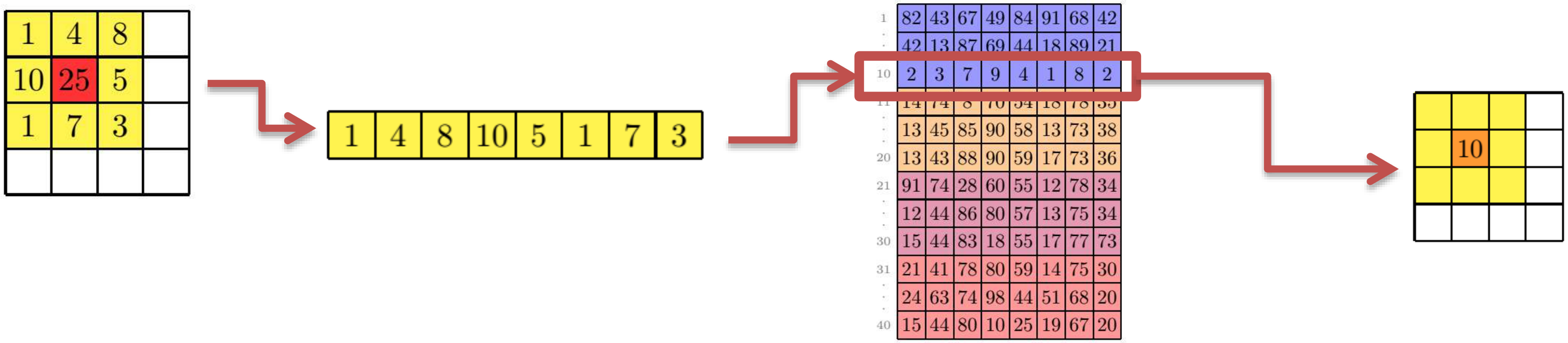
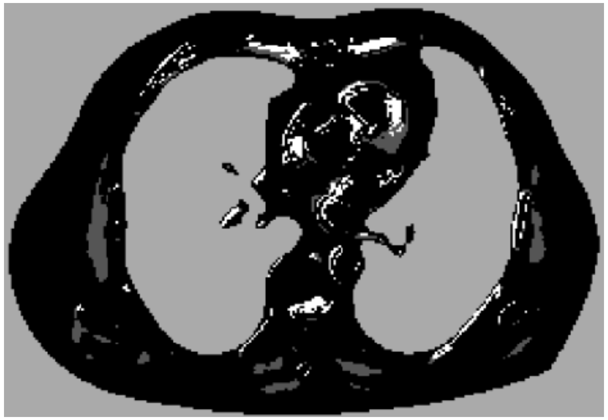
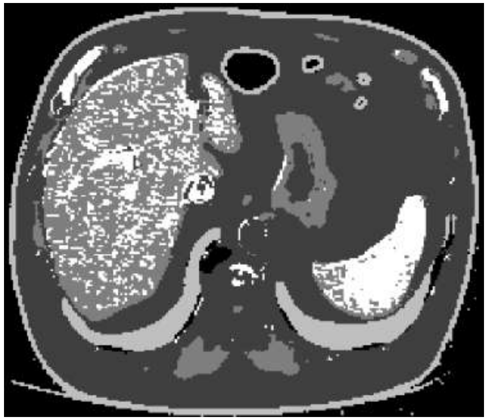
Segmentation



7.1 Segmentation: Methodology

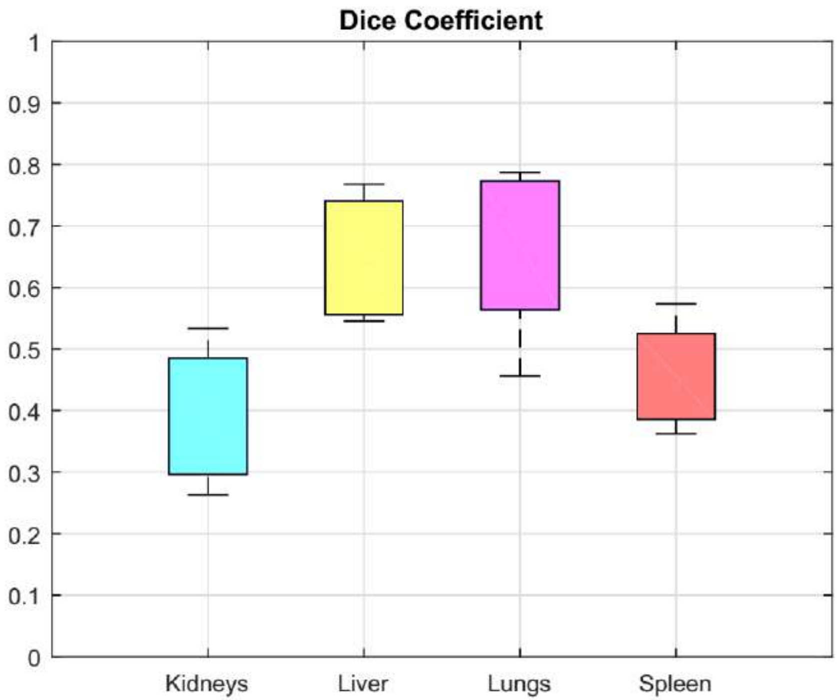


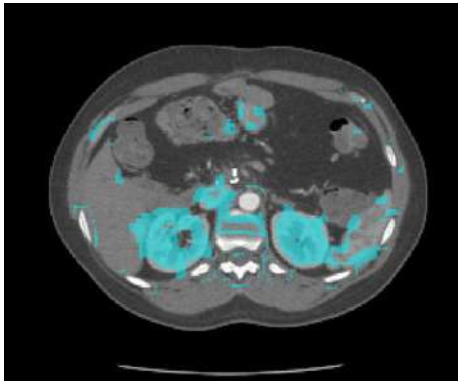




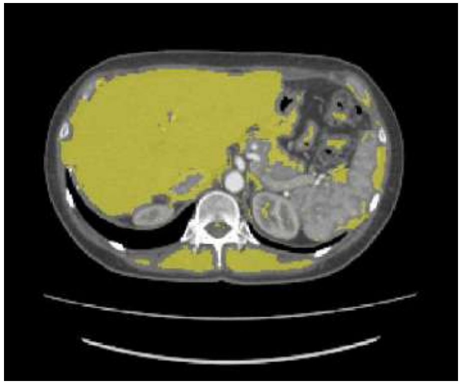
- Neighbourhood size
- Dictionary size
- Majority Voting Scheme
- Morphological Operations
- Adaptive Threshold
- Background Information

7.2 Segmentation: Results

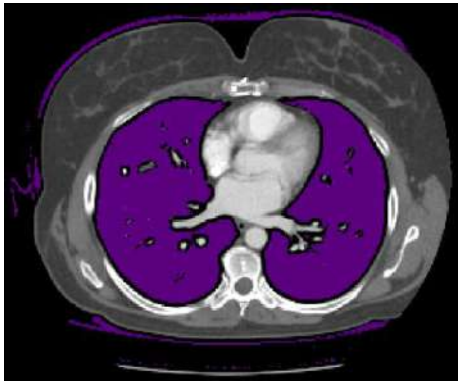




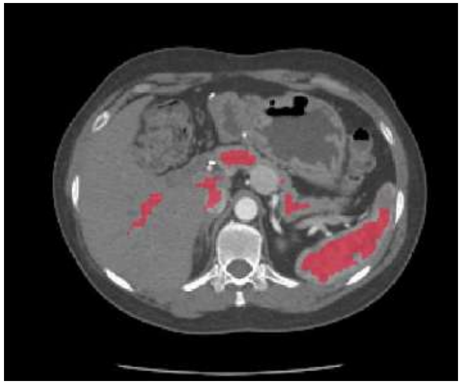
Background information and adaptive threshold of 605



Morphological operations and adaptive threshold of 605



Adaptive threshold of 1352



Threshold corresponding to the 25th percentile of the máximum distance per slice

8. Conclusions

- The implemented texture features were reassuringly robust to the noise level and AIDR3D noise reduction.
- These results were compared to the accuracy obtained using statistical texture methods. The results showed that our MRF-based method is more robust in noisy datasets.
- Our proposed Euclidean distance as metric to compared histograms performed consistently better on these datasets
- Classification of individual pixels had poorer performance than region classification. In general, the use of larger neighbourhoods, smaller dictionary sizes, morphological closing, and background textons presented the best results.

9. Future Work

- The first and most obvious step is the use of three-dimensional texton neighbourhoods.
- Another possible improvement is the inclusion of rotationally invariant features.
- A more complex addition might be the use of a sparse modelling approach to find representative objects
- Future work should evaluate the use of these features in differentiating healthy and unhealthy tissue

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10. Bibliography

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