Optimal Image Representations For Mass Detection In Digital Mammography

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Medical Imaging Group

June 1, 2005

Outline

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Breast Cancer – Definition

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Breast cancer $\mapsto$ malignant tumor developed from cells of the breast

Breast Cancer – Signs

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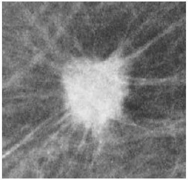
Masses



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with size 3–30 (mm)

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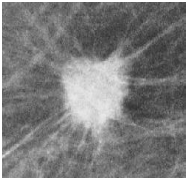

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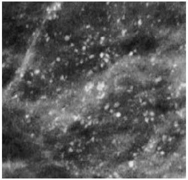
Micro–calcifications



small spots in the breast tissue with size 0.1–0.3 (mm)

Breast Cancer – Incidence And Mortality

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$\Rightarrow$ Screening mammography: earlier detection through periodical X-ray breast examination performed on asymptomatic patients is fundamental

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The left and right breasts of the patient are both exposed to X–rays. . .

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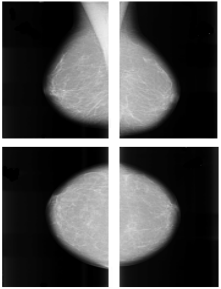
. . . and mammographic digital images are obtained for each breast at different views



Screening Mammography – Radiologists' Detection

The radiologist looks carefully at each mammographic digital image. . .

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...and marks the regions suspected to be potential breast tumors

Screening Mammography – Radiologists' Performances

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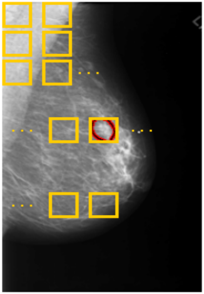
⇒ Computer–Aided Detection (CAD) systems are commonly used as second readers to increase the efficiency of screening procedures

Screening Mammography – Computer–Aided Detection

In order to automatically implement mass detection, first each mammographic digital image must be scanned...



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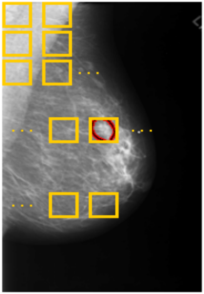
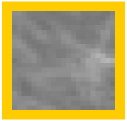


...then for each scanned region (a.k.a. crop)



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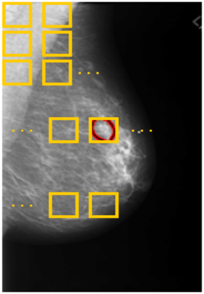

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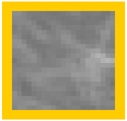

What is that?
A mass or a non–mass?

Outline

1. Digital Mammography
2. Two–Class Pattern Classification
3. Exploring Image Representations
4. CAD System Implementation

Problem Set Up – Flow Diagram

The Two Classes

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The Two Classes $\mapsto$

Problem Set Up – Flow Diagram

The Two Classes $\mapsto$ **Features**

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The Two Classes $\longmapsto$ **Features** $\longmapsto$ **Classifier**

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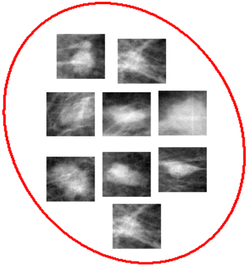

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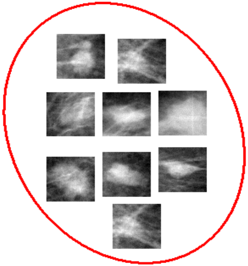
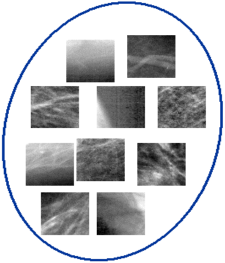


Non–mass class



Features – Flow Diagram

The Two Classes

- Masses
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$\mapsto$ **Features** $\mapsto$ **Classifier**

Features – Pixels, Wavelets, Ranklets

Features should be chosen as to emphasize discriminant characteristics of the two classes

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(Much more details in the next section. . .)

Classifier – Flow Diagram

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$\longmapsto$

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Classifier

Classifier – Notation

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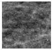
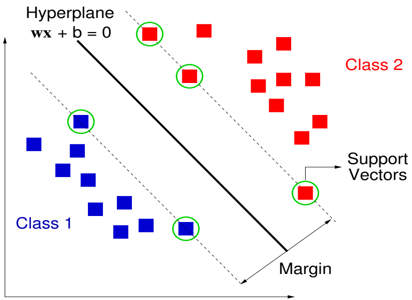
Non–mass	-1	

Classifier – Support Vector Machine

SVM is a classifier which finds the hyperplane $\mathbf{w} \cdot \mathbf{x} + b = 0$ maximizing the margin between the two classes in the training set

Train



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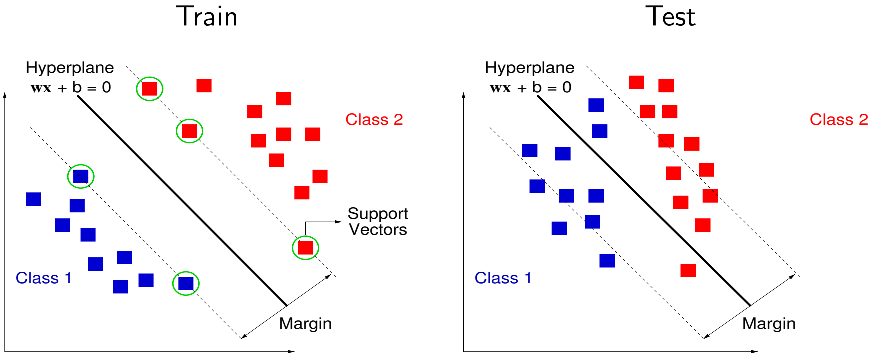

Classifier – SVM's Kernels

Once SVM has been trained, each new sample $\mathbf{x}$ is classified according to:

$$f(\mathbf{x}) = sign\left(\sum_{i=1}^{l} \alpha_i y_i K(\mathbf{x}, \mathbf{x}_i) + b\right)$$

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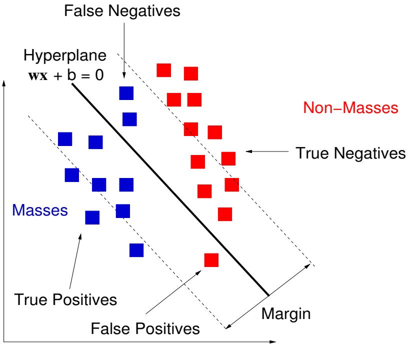
- Radial basis kernel:

$$K(\mathbf{x}, \mathbf{y}) = \exp\left(-\gamma \left\|\mathbf{x} - \mathbf{y}\right\|^2\right)$$

Classifier – Performances

After SVM has been tested on the samples of the test set. . .



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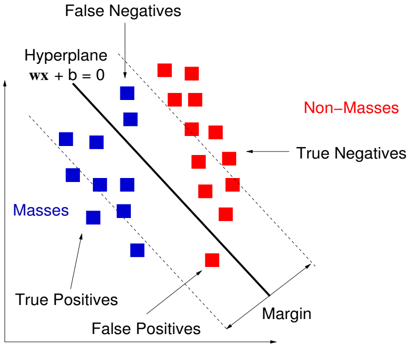
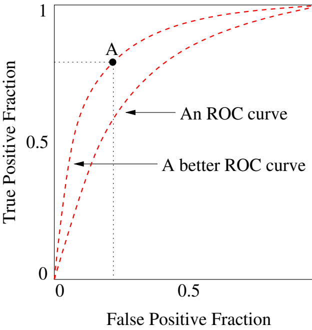


. . . then classification performances are given by using ROC curves



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The Two Classes

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- Non–masses

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Features

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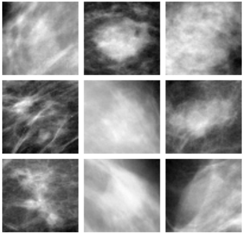

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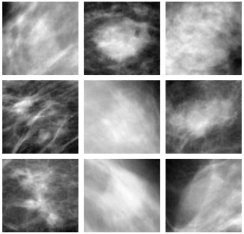

⇒ Objective difficulty of characterizing all types of masses with the same few measurable quantities (features)

Overview – Featureless Approach

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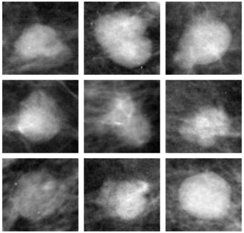

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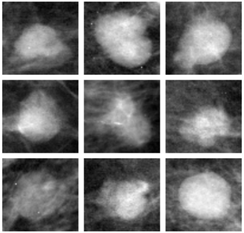

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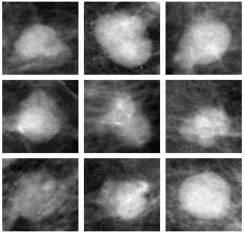

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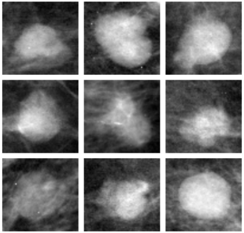

Adopted approach:

- in order to deal with almost every type of masses, raw/enhanced crops are classified without extracting any a priori feature $\mapsto$ featureless approach

Overview – Material And Methods

USF Digital Database for Screening Mammography (DDSM):

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- 1000 crops representing masses

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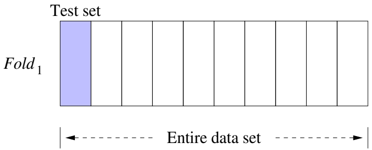


Pixels – Flow Diagram

The Two Classes

- Masses
- Non–masses

$\mapsto$

Features

- Pixels
- Wavelets
- Ranklets

$\mapsto$

Classifier

- SVM

Pixels – Motivation

Why pixel–based image representations?

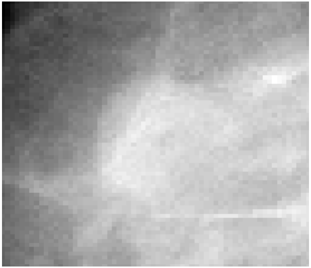
Pixels – Motivation

Why pixel–based image representations?

- To investigate whether the gray–level values of the crops gives enough informations in order to discriminate between masses and non–masses

Pixels – Definition

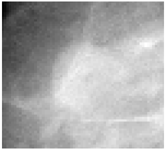
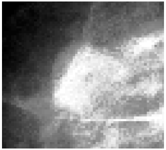
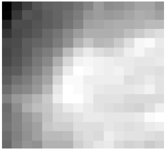
A crop...



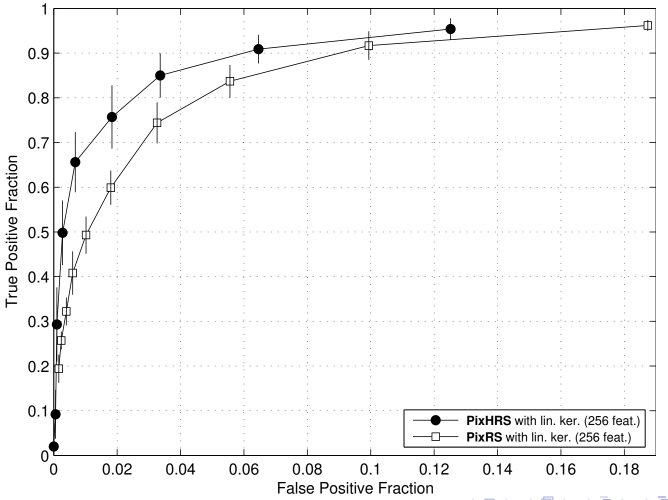
...and its gray–level values

$$\begin{pmatrix} 0 & 0 & \dots & 201 \\ 0 & 0 & \dots & 203 \\ 0 & 0 & \dots & 201 \\ \vdots & \vdots & \vdots & \vdots \\ 147 & 171 & \dots & 237 \\ 152 & 205 & \dots & 237 \\ 152 & 225 & \dots & 232 \end{pmatrix}$$

Pixels – Example

Original crop	Equalized crop	Resized crop
		

Pixels – ROC Curve (Linear Kernel)



Pixels – Some Numerical Results

	$FPF \sim .01$	$FPF \sim .03$	$FPF \sim .05$
PixHRS	$.70 \pm .06$	$.84 \pm .05$	$.89 \pm .03$
PixRS	$.49 \pm .04$	$.72 \pm .05$	$.82 \pm .04$

Table: Classification results comparison. The *TPF* values obtained by the best performing pixel–based image representations are shown, in particular for *FPF* values approximately equal to .01, .03 and .05

Wavelets – Flow Diagram

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Wavelets – Motivation

Why wavelet–based image representations?

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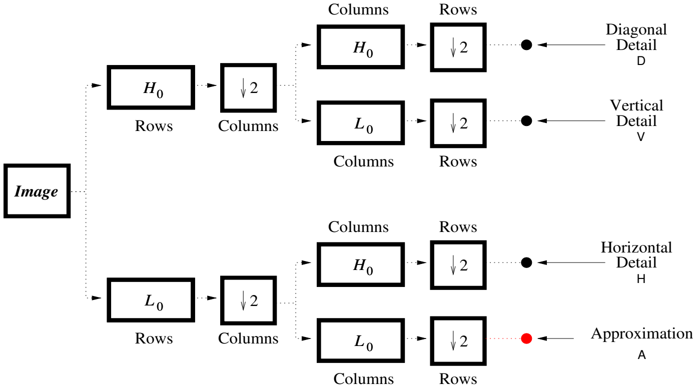
Why wavelet–based image representations?

- To evaluate whether their ability in enhancing edges and boundaries improve the discrimination between masses and non–masses

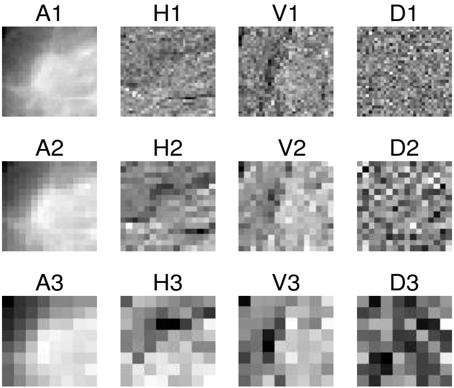
Wavelets – Definition

2D discrete wavelet transform (1–level decomposition):



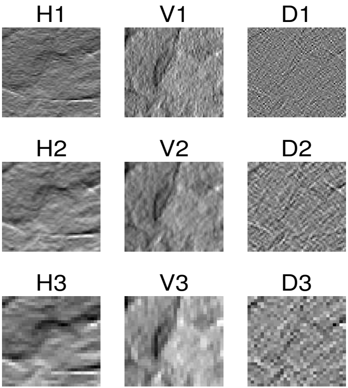
Wavelets – Example (Discrete Wavelet Transform)

2D discrete wavelet transform (3–level decomposition):

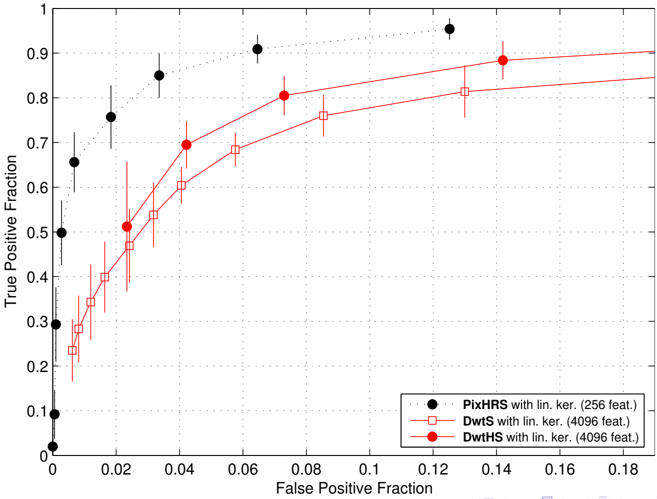


Wavelets – Example (Overcomplete Wavelet Transform)

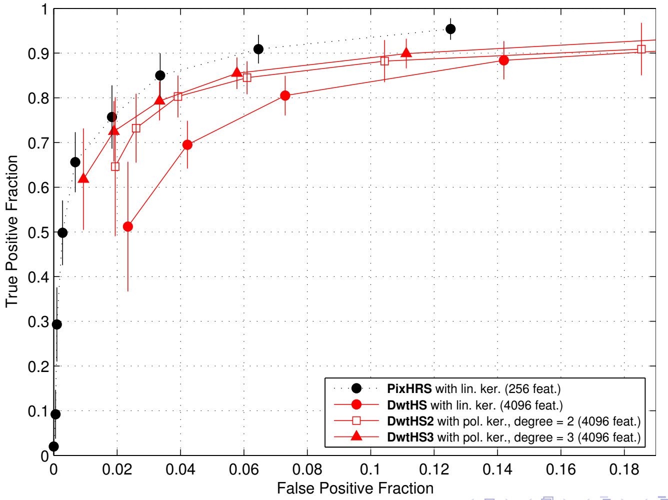
2D overcomplete wavelet transform (3–level decomposition):



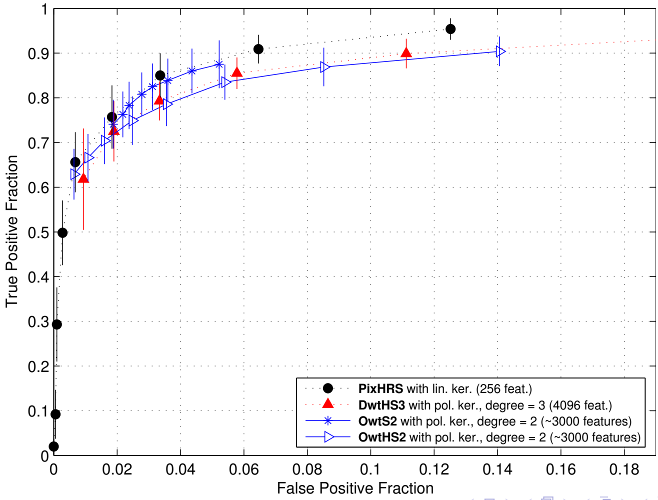
Wavelets – ROC Curve (DWT, Linear Kernel)



Wavelets – ROC Curve (DWT, Polynomial Kernel)



Wavelets – ROC Curve (OWT, Polynomial Kernel)



Wavelets – Some Numerical Results

	$FPF \sim .01$	$FPF \sim .03$	$FPF \sim .05$
PixHRS	$.70 \pm .06$	$.84 \pm .05$	$.89 \pm .03$
OwtS2	-	$.82 \pm .05$	$.87 \pm .05$
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Table: Classification results comparison. The *TPF* values obtained by the best performing pixel–based, DWT–based and OWT–based image representations are shown, in particular for *FPF* values approximately equal to .01, .03 and .05

Ranklets – Flow Diagram

The Two Classes

- Masses
- Non–masses

↦

Features

- Pixels
- Wavelets
- Ranklets

↦

Classifier

- SVM

Ranklets – Motivation

Why ranklet–based image representations?

Ranklets – Motivation

Why ranklet–based image representations?

- To evaluate whether their non–parametricity improve the discrimination between masses and non–masses

Ranklets – Definition

Ranklets are features modeled on Haar wavelets

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Properties:

Ranklets – Definition

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Properties:

- orientation selective

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Properties:

- orientation selective
- non–parametric

Ranklets – Definition

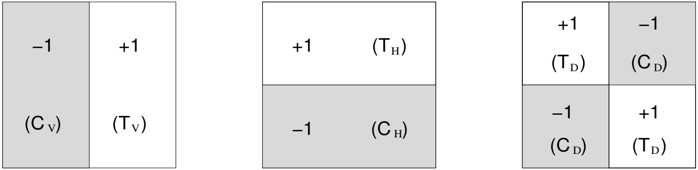
Ranklets are features modeled on Haar wavelets

Properties:

- orientation selective
- non–parametric
- multi–resolution

Ranklets – Orientation Selective Property

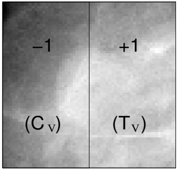
The Haar wavelet supports are defined:



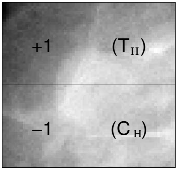
Vertical | Horizontal | Diagonal

Ranklets – Orientation Selective Property

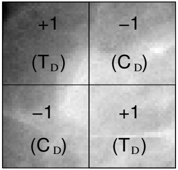
The Haar wavelet supports are defined:



Vertical



Horizontal



Diagonal

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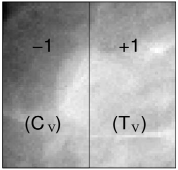
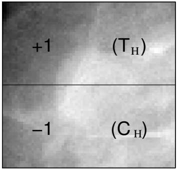
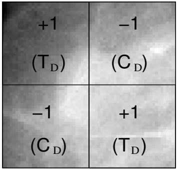


Vertical



Horizontal



Diagonal

Then:

Ranklets – Orientation Selective Property

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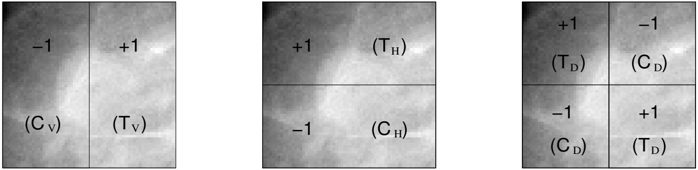

Vertical Horizontal Diagonal

Then: How many pixel pairs $(\mathbf{p}_m, \mathbf{p}_n)$ with $\mathbf{p}_m \in T_j$ and $\mathbf{p}_n \in C_j$ such that Intensity$(\mathbf{p}_m) >$ Intensity$(\mathbf{p}_n)$?

Ranklets – Non–Parametric Property

The ranklet coefficients are computed:

$$R_j = \frac{\sum_{\mathbf{p} \in \mathrm{T}_j} \mathrm{Rank}^{\mathrm{C}_j \cup \mathrm{T}_j}(\mathbf{p}) - \frac{N}{4}\left(\frac{N}{2}+1\right)}{\frac{N^2}{8}} - 1, \quad j = \mathrm{V},\ \mathrm{H},\ \mathrm{D}$$

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- Number of pixel pairs $(\mathbf{p}_m, \mathbf{p}_n) \in (\mathrm{T}_j \times \mathrm{C}_j)$ such that $\mathrm{Intensity}(\mathbf{p}_m) > \mathrm{Intensity}(\mathbf{p}_n)$. Possible values $\in [0, \frac{N^2}{4}]$

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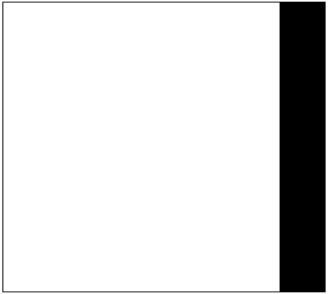
- $R_j \sim +1$ if pixels in T_j have intensity values $>$ than C_j
  $R_j \sim -1$ if pixels in T_j have intensity values $<$ than C_j

Ranklets – Example

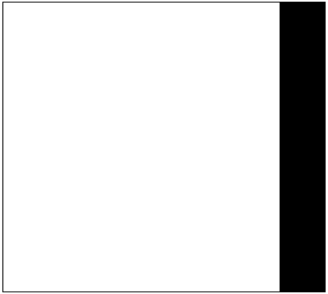
Synthetic image



$$R_{\mathrm{V,H,D}} = [-0.28, 0, 0]$$

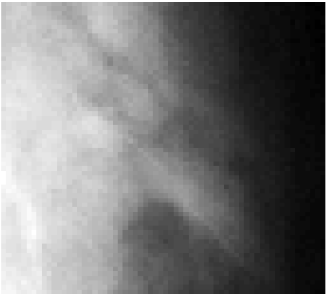
Ranklets – Example

Synthetic image



$$R_{\mathrm{V,H,D}} = [-0.28, 0, 0]$$

Real image

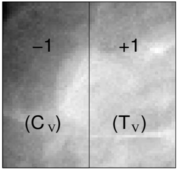


$$R_{\mathrm{V,H,D}} = [-0.98, -0.08, 0.06]$$

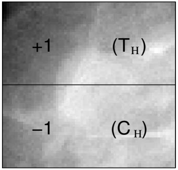
Ranklets – Multi–Resolution Property

The ranklet coefficients can be calculated at different resolutions:

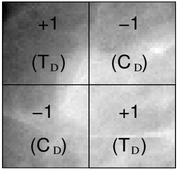
Resolution 1:



Vertical



Horizontal

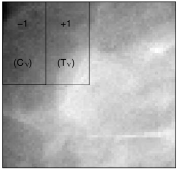


Diagonal

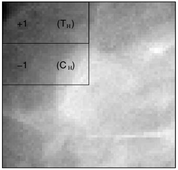
Ranklets – Multi–Resolution Property

The ranklet coefficients can be calculated at different resolutions:

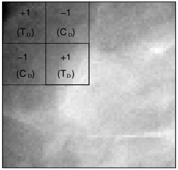
Resolution 2:



Vertical



Horizontal



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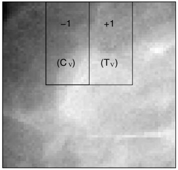
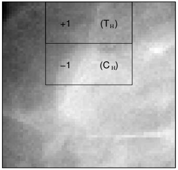
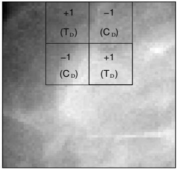


Vertical



Horizontal



Diagonal

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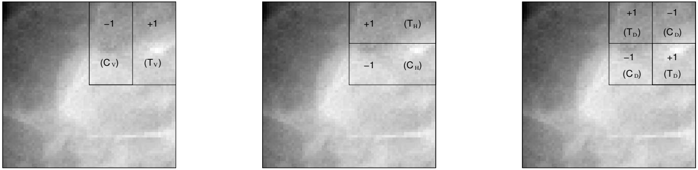

Vertical Horizontal Diagonal

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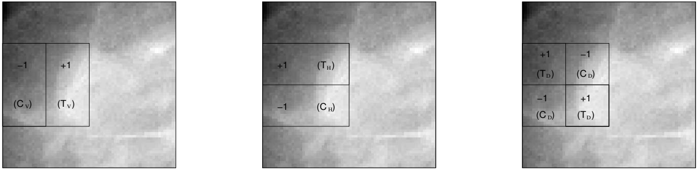

Vertical Horizontal Diagonal

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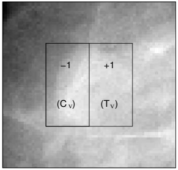
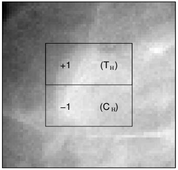
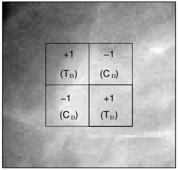


Vertical



Horizontal



Diagonal

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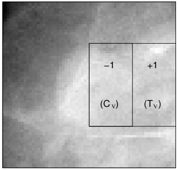
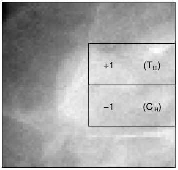
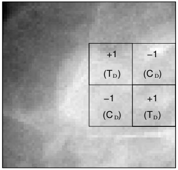


Vertical



Horizontal



Diagonal

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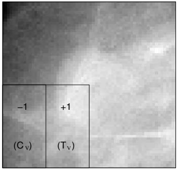
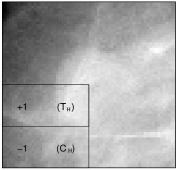
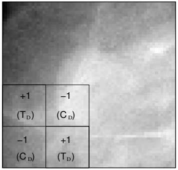


Vertical



Horizontal



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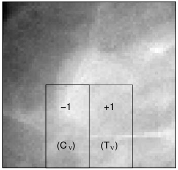
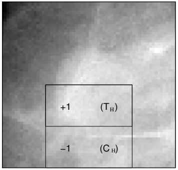
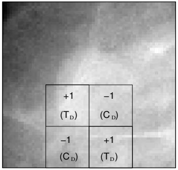


Vertical



Horizontal



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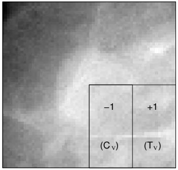
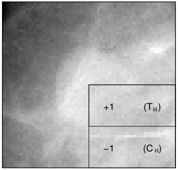
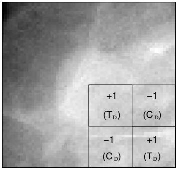


Vertical



Horizontal

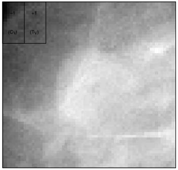


Diagonal

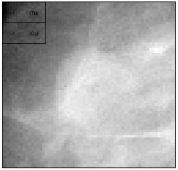
Ranklets – Multi–Resolution Property

The ranklet coefficients can be calculated at different resolutions:

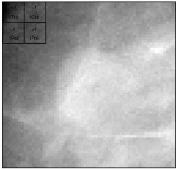
Resolution 3:



Vertical

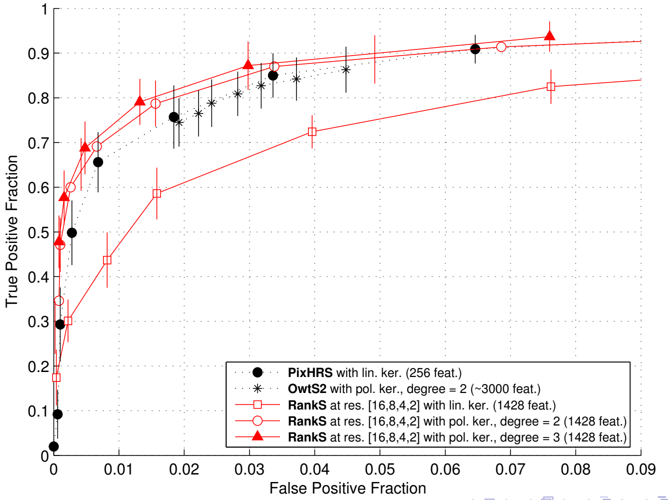


Horizontal

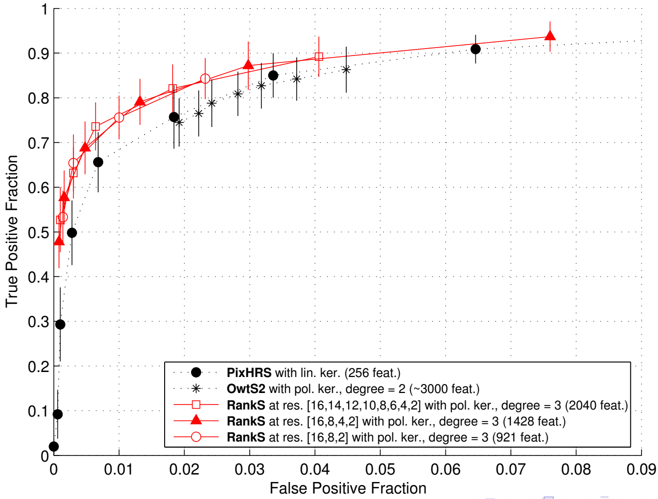


Diagonal

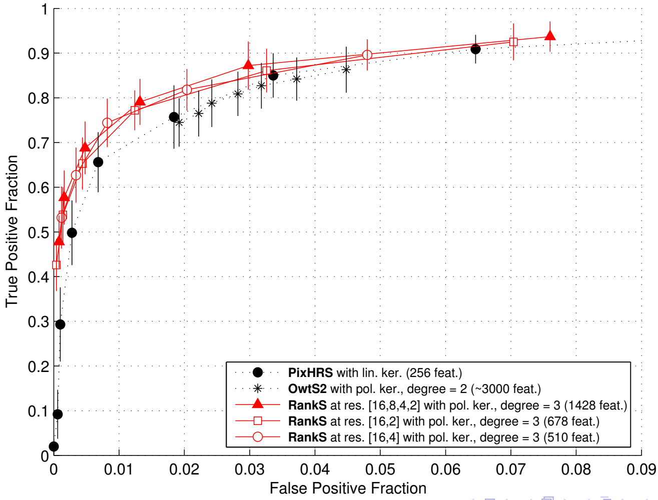
Ranklets – ROC Curve (Varying Kernels)



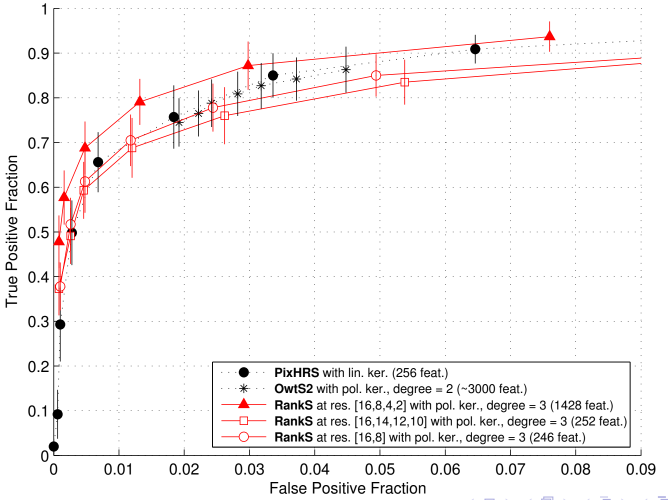
Ranklets – ROC Curve (All Resolutions)



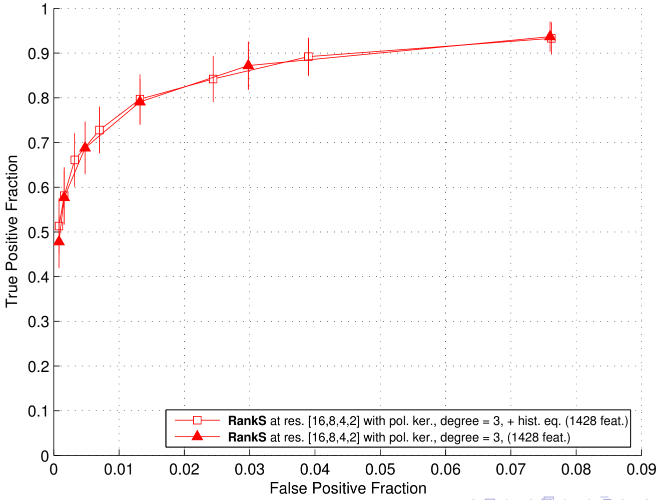
Ranklets – ROC Curve (Low + High Resolutions)



Ranklets – ROC Curve (Low + Intermediate Resolutions)



Ranklets – ROC Curve (Histogram Equalization)



Ranklets – Some Numerical Results

	$FPF \sim .01$	$FPF \sim .03$	$FPF \sim .05$
RankS3	$.76 \pm .05$	$.87 \pm .05$	$.91 \pm .04$
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Table: Classification results comparison. The *TPF* values obtained by the best performing pixel–based, DWT–based, OWT–based and ranklet–based image representations are shown, in particular for *FPF* values approximately equal to .01, .03 and .05

Ranklets – Recursive Feature Elimination

RFE is a method for eliminating features responsible of small changes in the classifier's cost function $\mapsto$ feature reduction

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SVM's cost function:

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1. SVM is trained and tested with the actual set of ranklet coefficients

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RFE iterative implementation:

1. SVM is trained and tested with the actual set of ranklet coefficients
2. the variation ΔJ is computed by removing singularly each ranklet coefficient
3. the ranklet coefficient corresponding to the smallest ΔJ is removed

Ranklets – RFE + Cross–Validation

RFE iterative implementation combined to cross–validation:

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RFE iterative implementation combined to cross–validation:

1. Train SVM for each fold

Ranklets – RFE + Cross–Validation

RFE iterative implementation combined to cross–validation:

1. Train SVM for each fold
2. Test SVM for each fold

Ranklets – RFE + Cross–Validation

RFE iterative implementation combined to cross–validation:

1. Train SVM for each fold
2. Test SVM for each fold
3. Compute the ranking criterion for each feature in each fold

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RFE iterative implementation combined to cross–validation:

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2. Test SVM for each fold
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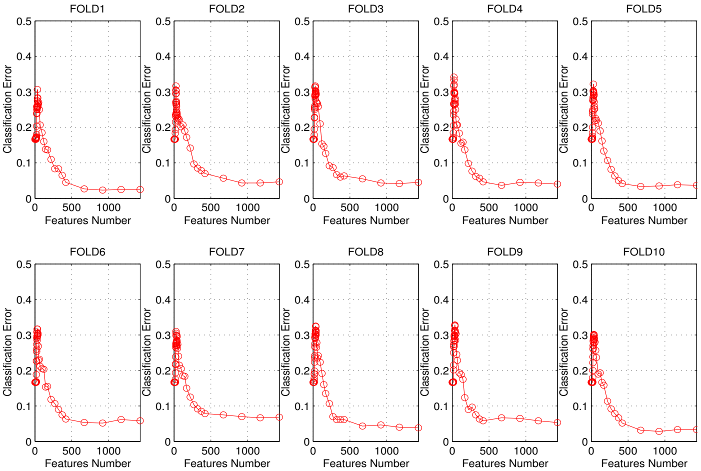
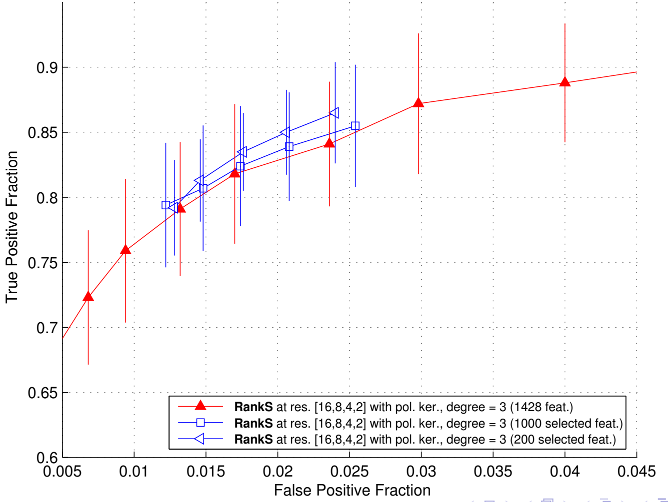
4. Compute a ranking list, common to all folds, by averaging the ranking position of each feature in each fold
5. Remove the feature with the smallest rank in the ranking list

Ranklets – RFE (Error)

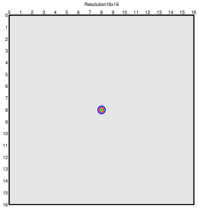


Ranklets – RFE (ROC Curve)

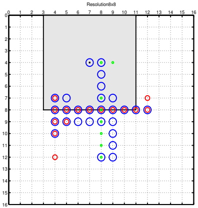


Ranklets – RFE (500 Most Important Ranklet Coeffs)

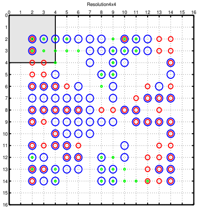
Reducing the number of ranklet coefficients from 1428 to 500 by means of RFE:



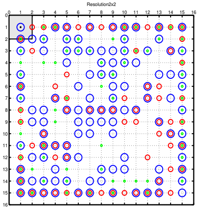
Res. 16×16



Res. 8×8



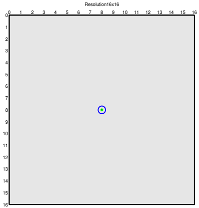
Res. 4×4



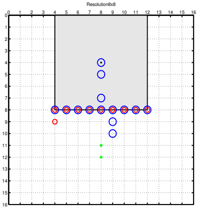
Res. 2×2

Ranklets – RFE (300 Most Important Ranklet Coeffs)

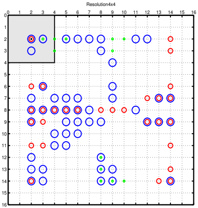
Reducing the number of ranklet coefficients from 1428 to 300 by means of RFE:



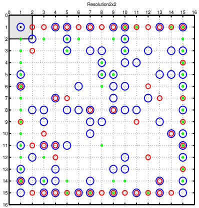
Res. 16 × 16



Res. 8 × 8



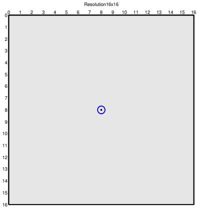
Res. 4 × 4



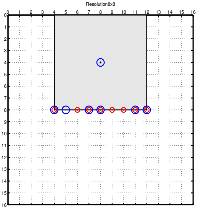
Res. 2 × 2

Ranklets – RFE (200 Most Important Ranklet Coeffs)

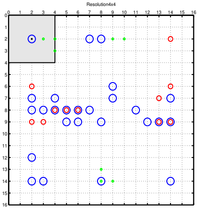
Reducing the number of ranklet coefficients from 1428 to 200 by means of RFE:



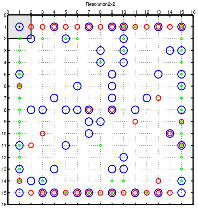
Res. 16×16



Res. 8×8



Res. 4×4



Res. 2×2

Ranklets – RFE (Considerations)

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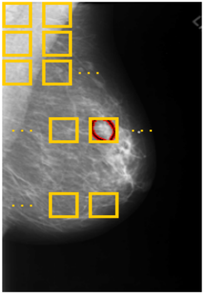
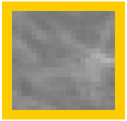
Outline

Overview – Remember?

In order to automatically implement mass detection, first each mammographic digital image must be scanned. . .



. . . then for each scanned region (a.k.a. crop)



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What else in order to have a complete Computer–Aided Detection (CAD) system for mass detection?

CAD Scheme – Steps

Proposed scheme:

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1. Segmentation

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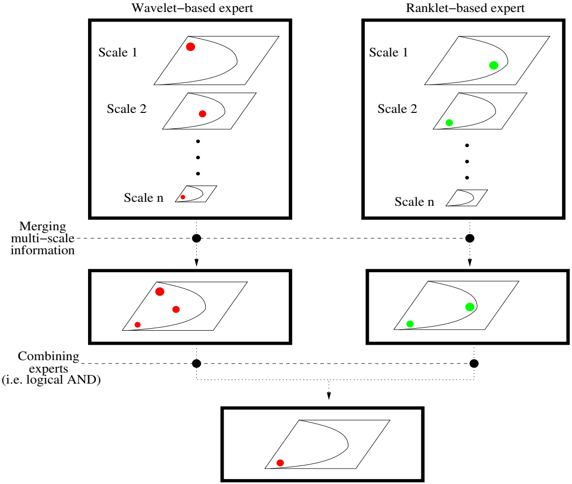
5. Prompted image

CAD Scheme – Flow Diagram



Prompted image

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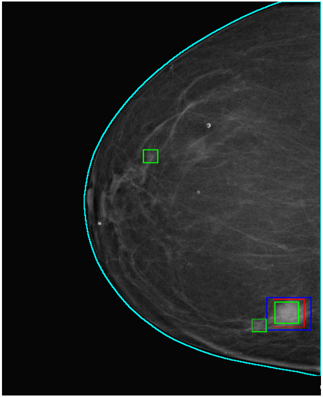
Results – Example 1

After merging multi–scale findings. . .



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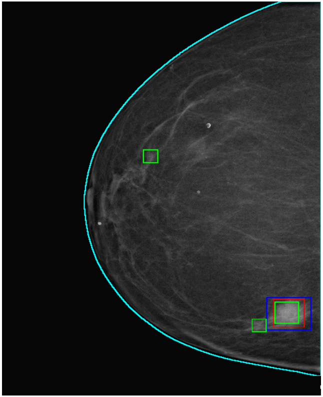

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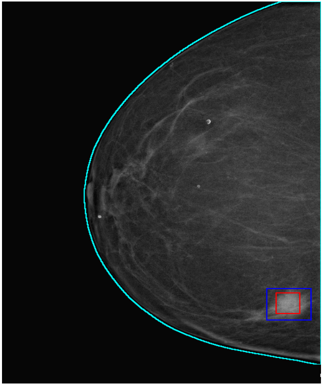
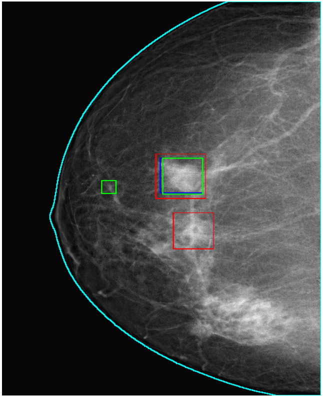


Results – Example 2

After merging multi–scale findings. . .



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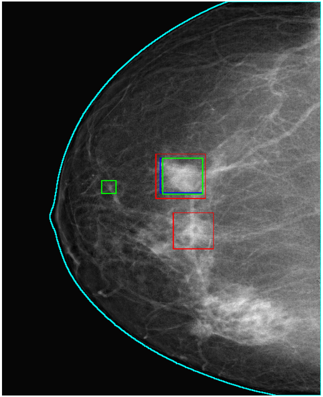

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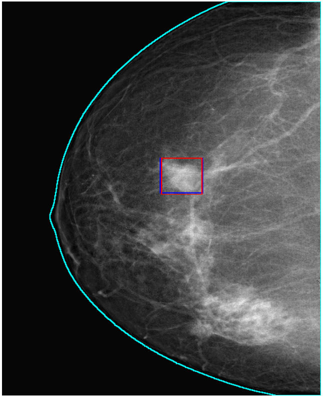
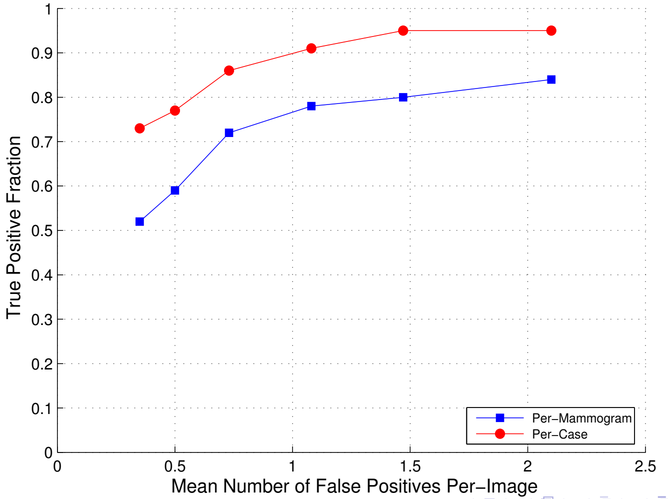


Results – FROC Curve



Results – Some Numerical Results

n_{Wav}	2	2	3	3	5	10
n_{Rank}	1	2	3	10	10	10
Mean number of false positives per–image	0.35	0.50	0.73	1.08	1.47	2.10
True positive fraction per–mammogram	0.52	0.59	0.72	0.78	0.80	0.84
True positive fraction per–case	0.73	0.77	0.86	0.91	0.95	0.95

Table: Performance of the proposed mass detection scheme

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CAD System Implementation

Combining wavelets and ranklets findings

Further Reading – Exploring Image Representations

- **M. Masotti**, *Exploring ranklets performances in mammographic mass classification using recursive feature elimination*, Submitted to International Conference on Image Processing, Genova, September 11-14, 2005
- **M. Masotti**, *A ranklet-based image representation for mass classification in digital mammograms*, Submitted to Pattern Recognition
- E. Angelini, R. Campanini, E. Iampieri, N. Lanconelli, **M. Masotti**, M. Roffilli, *Testing the performances of image representations for mass classification in digital mammograms*, Submitted to Image and Vision Computing

Further Reading – CAD System Implementation

- R. Campanini, D. Dongiovanni, E. Iampieri, N. Lanconelli, **M. Masotti**, G. Palermo, A. Riccardi, M. Roffilli *A novel featureless approach to mass detection in digital mammograms based on support vector machines*, Physics in Medicine and Biology, Vol. 49, No 6 (March 2004) 961-976
- R. Campanini, E. Angelini, D. Dongiovanni, E. Iampieri, N. Lanconelli, C. Mair-Noack, **M. Masotti**, G. Palermo, M. Roffilli, G. Saguatti, O. Schiaratura, *Preliminary results of a featureless CAD system on FFDM images*, International Workshop on Digital Mammography 2004 Proc., Durham, NC, USA, 18-21 June, 2004