Image processing mammography applications

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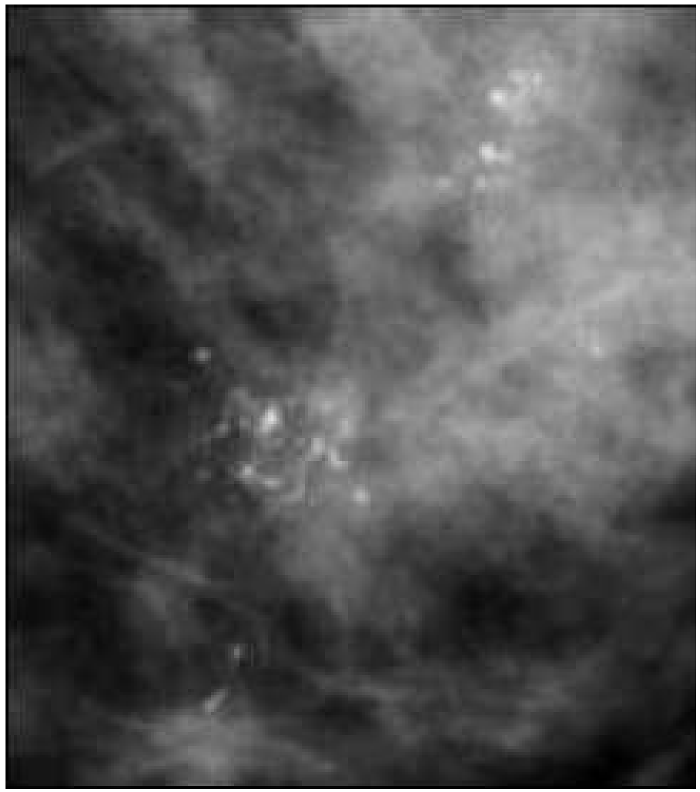
Image processing for mammography

1. Answering needs for systematic screening, diagnosis, interventional applications.
2. Several imaging modalities.
3. Here: focus on X-ray mammography and tomosynthesis.

A few words on imaging modalities

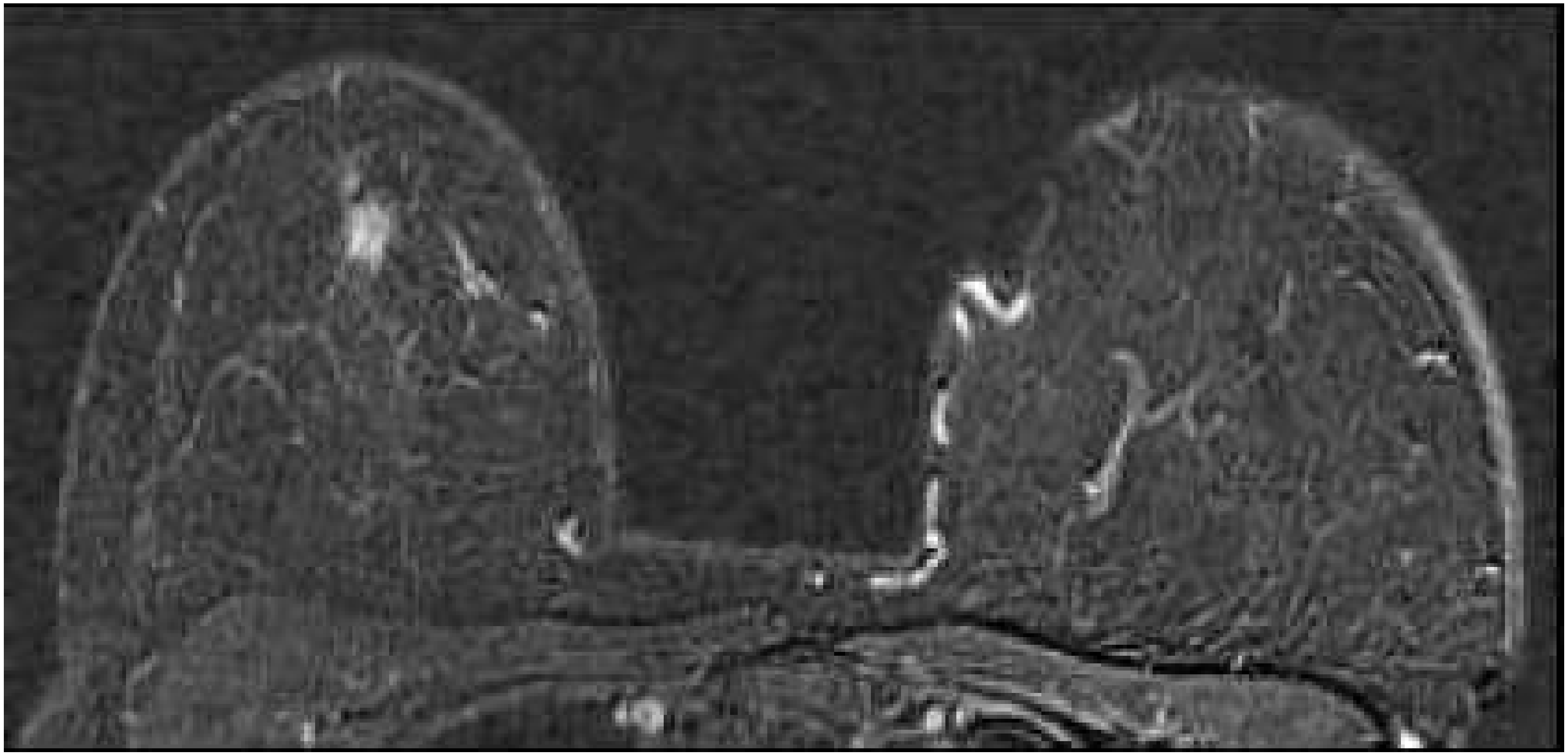


Mammography: capability to image microcalcifications

A few words on imaging modalities

Echography: lesion differentiation, needle guidance

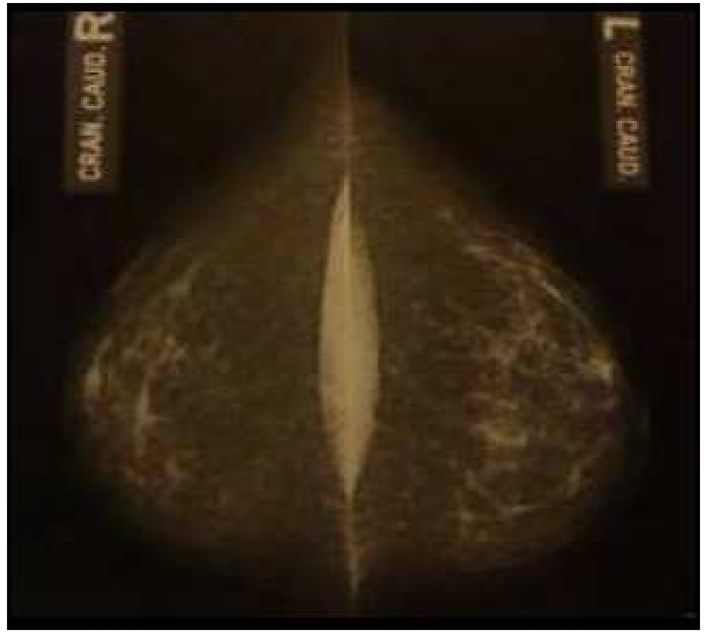
A few words on imaging modalities



MRI (using Gd): local extension assessment, diagnosis after treatment

Typical views

- cranio-caudal



- medio-lateral-oblique

Image processing chain

From native image... 

- Image correction:
  - gain / offset
  - defect pixels
  - modulation transfer function compensation
- Post-processing:
  - log transformation
  - thickness equalization
  - constrast enhancement
  - CAD
  - ...
- Display:
  - lighting
  - monitor calibration
  - VOI / LUT

... to visualization

Next: illustrations from S. Muller, GE Healthcare

Image correction

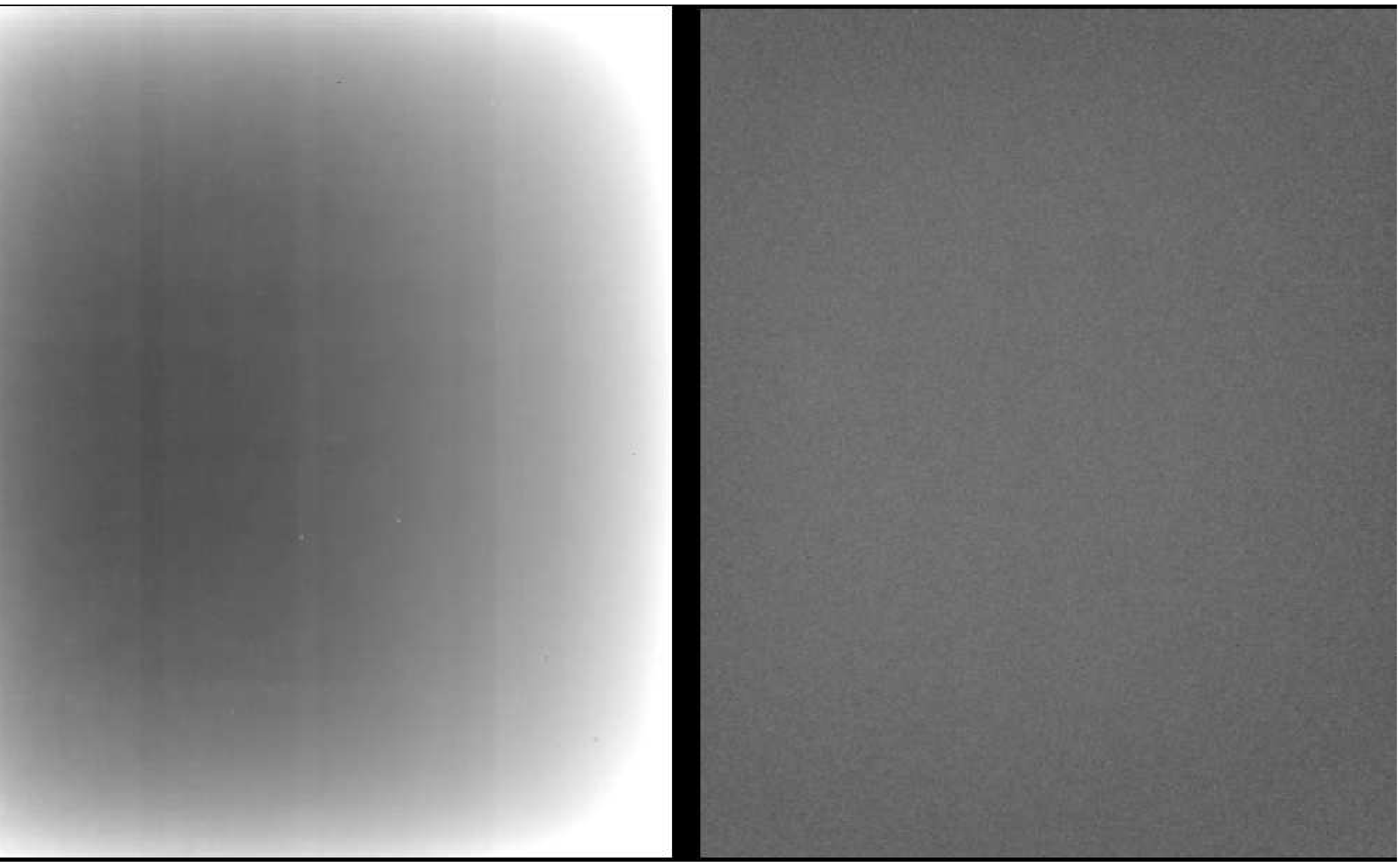
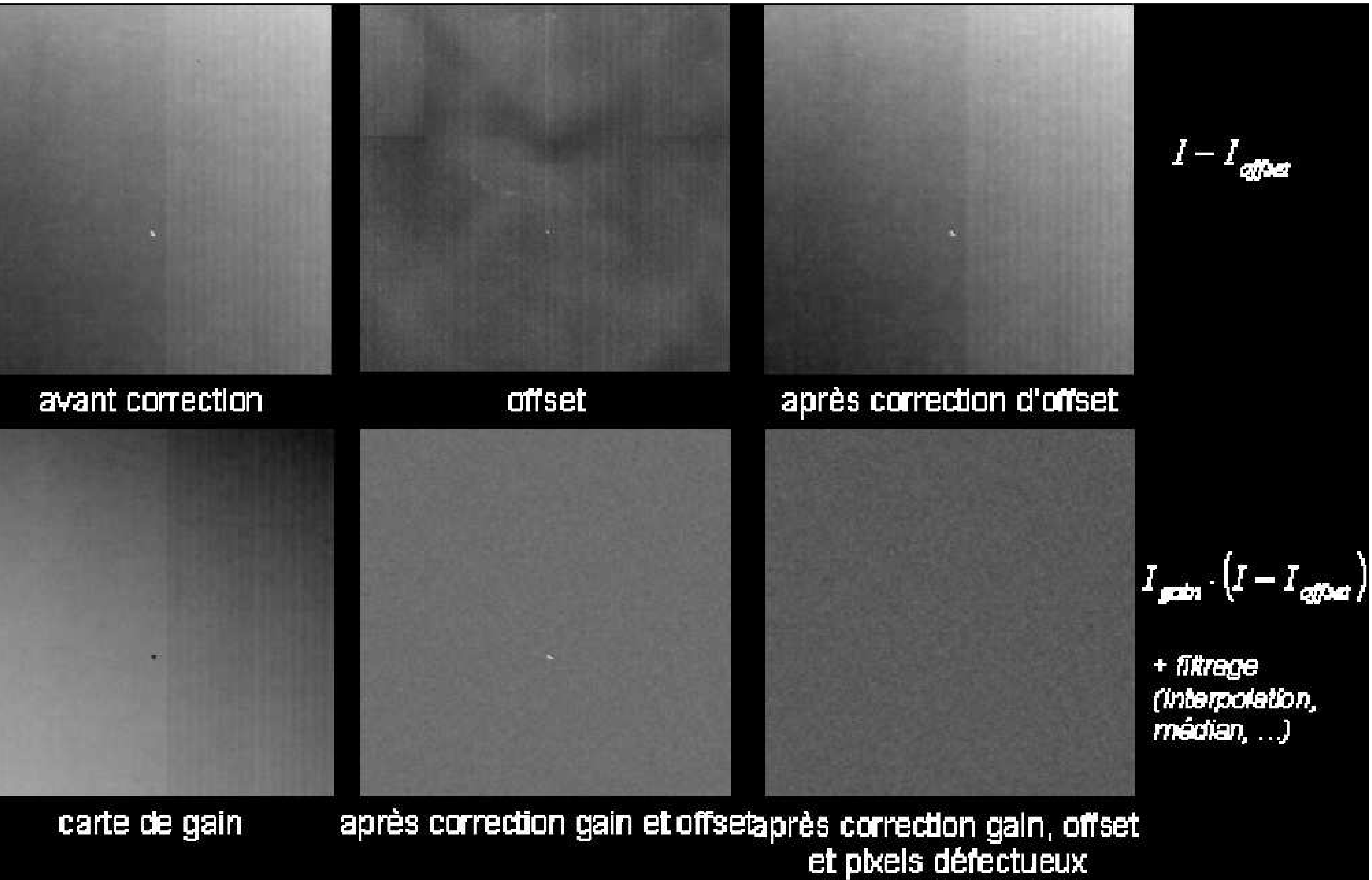
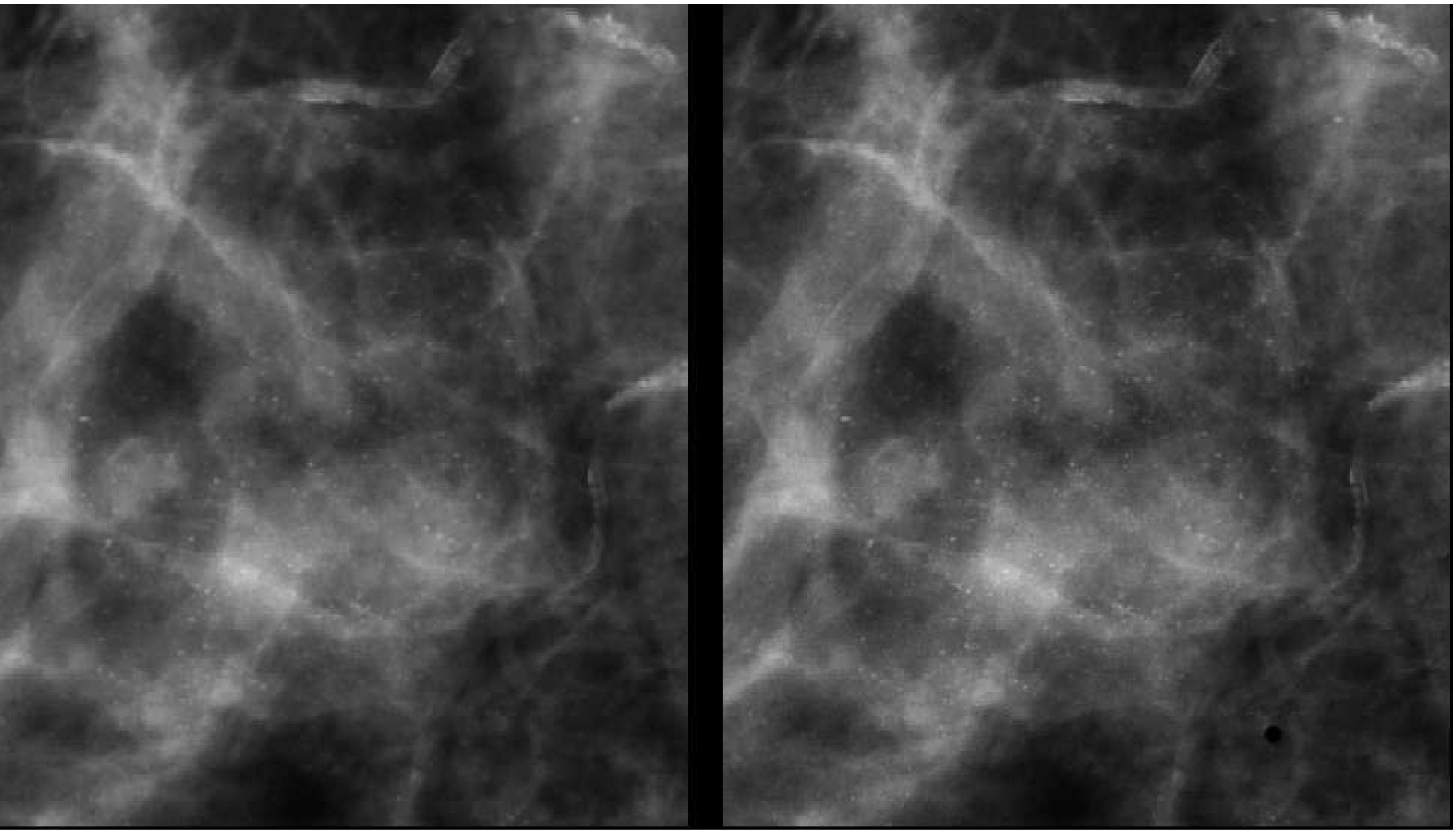


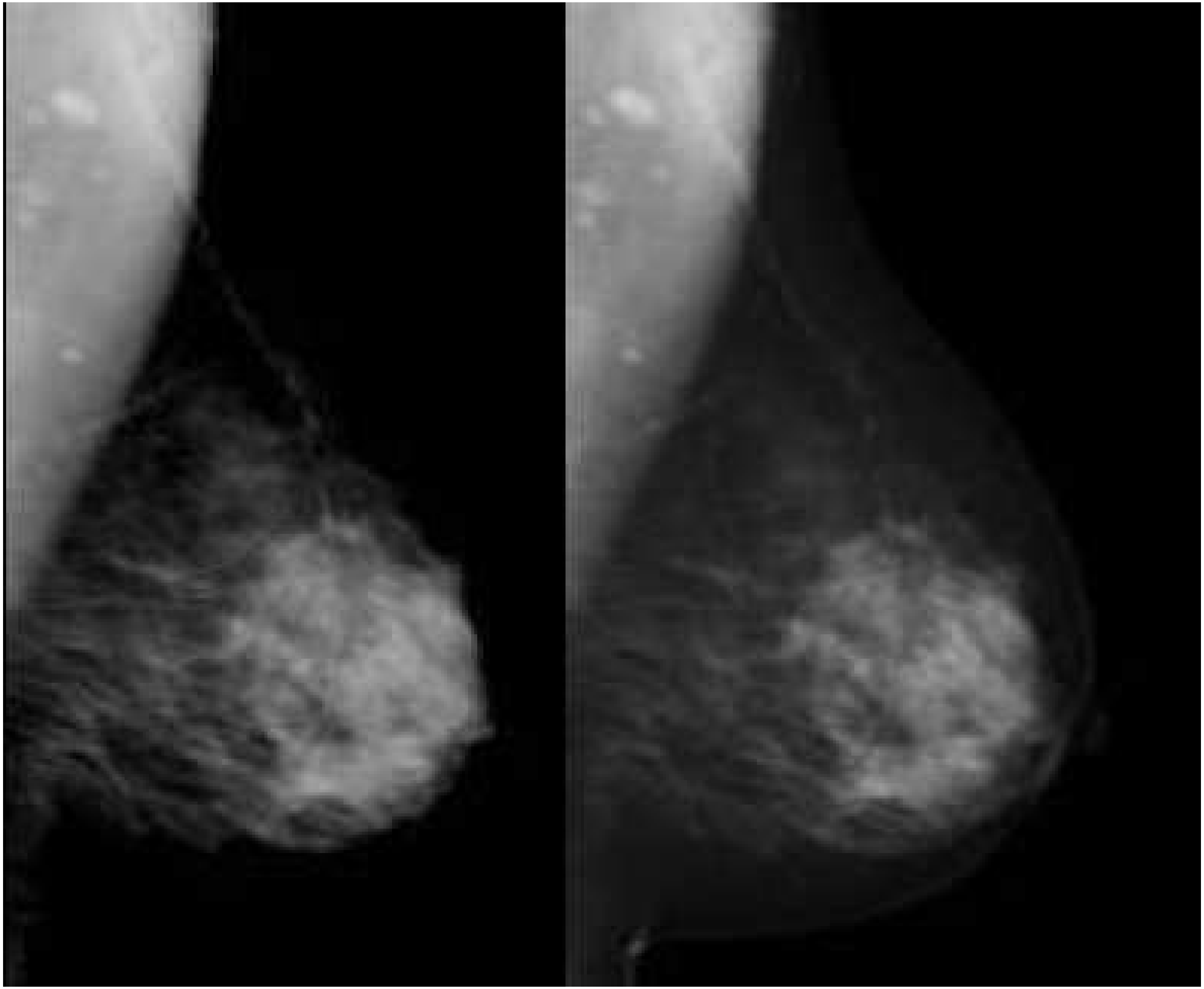
Image correction



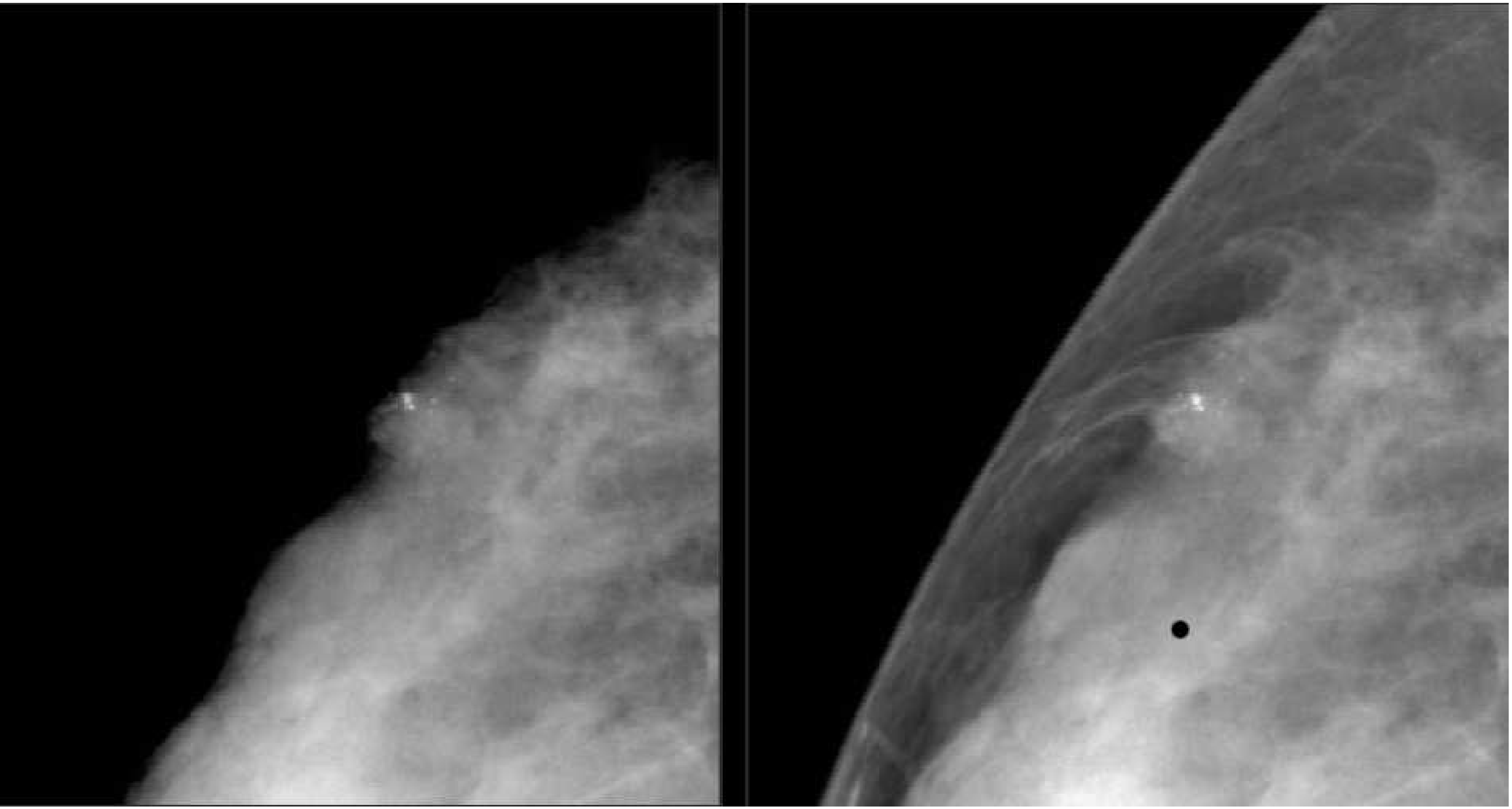
FTM compensation



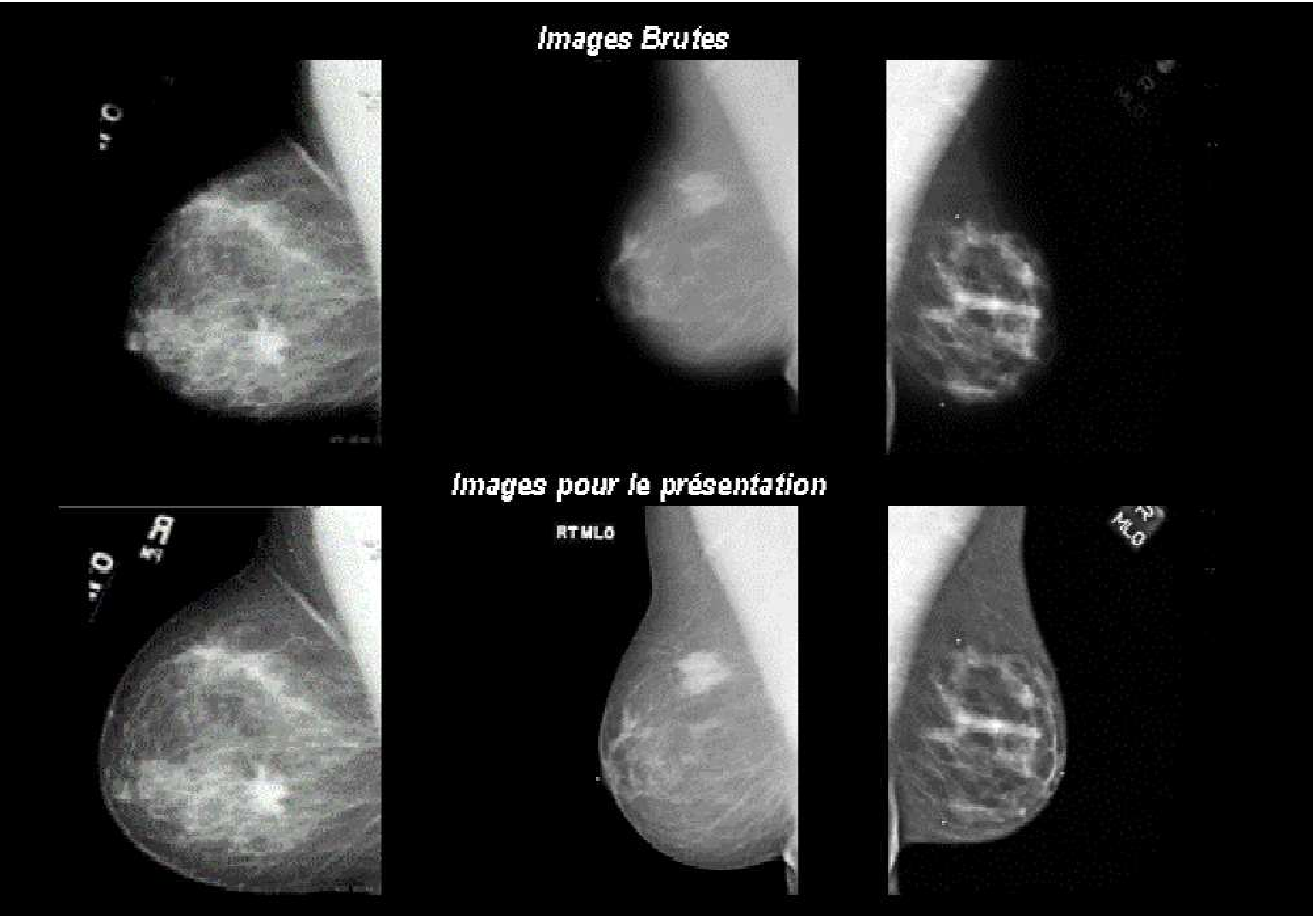
Thickness equalization



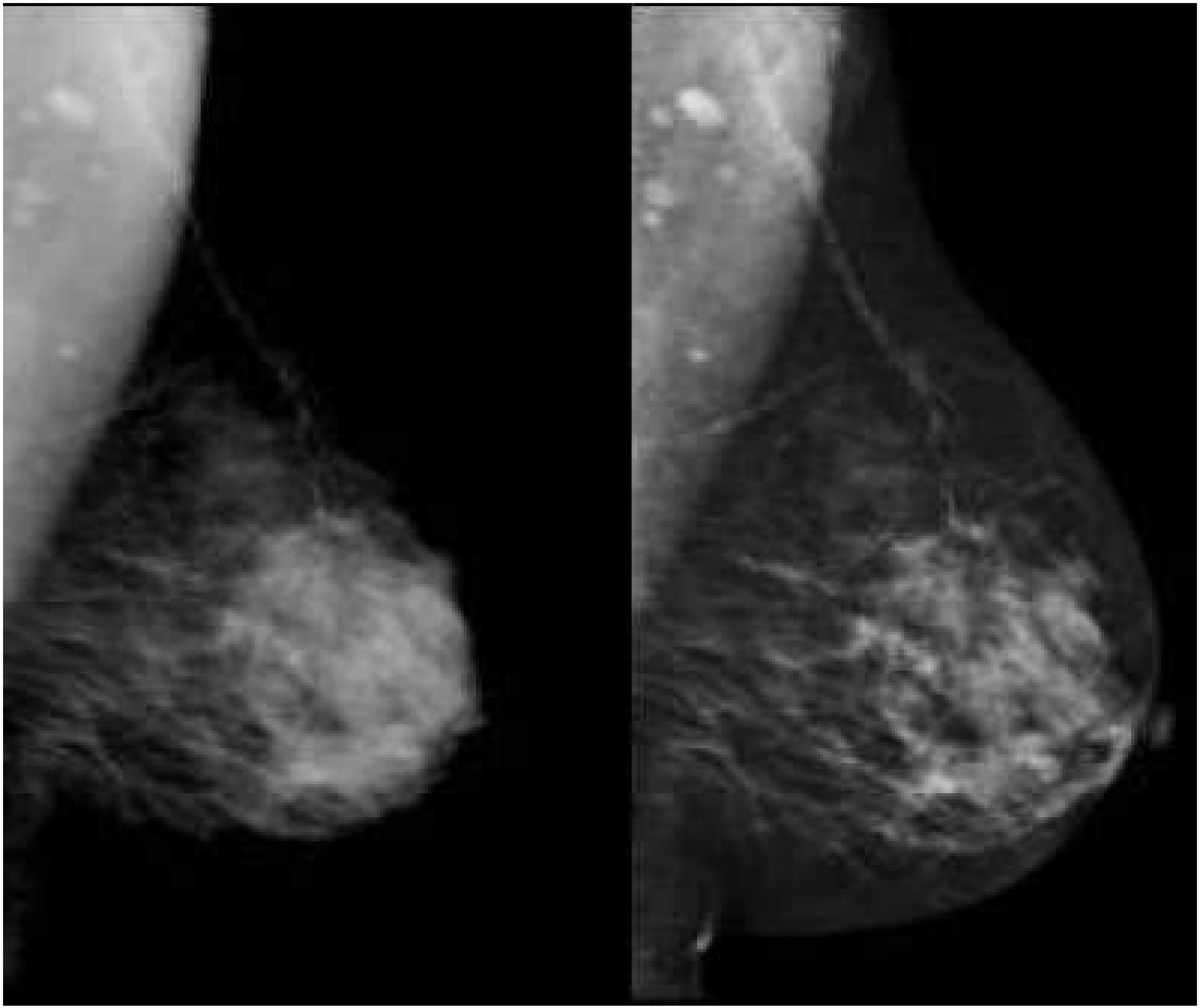
Thickness equalization



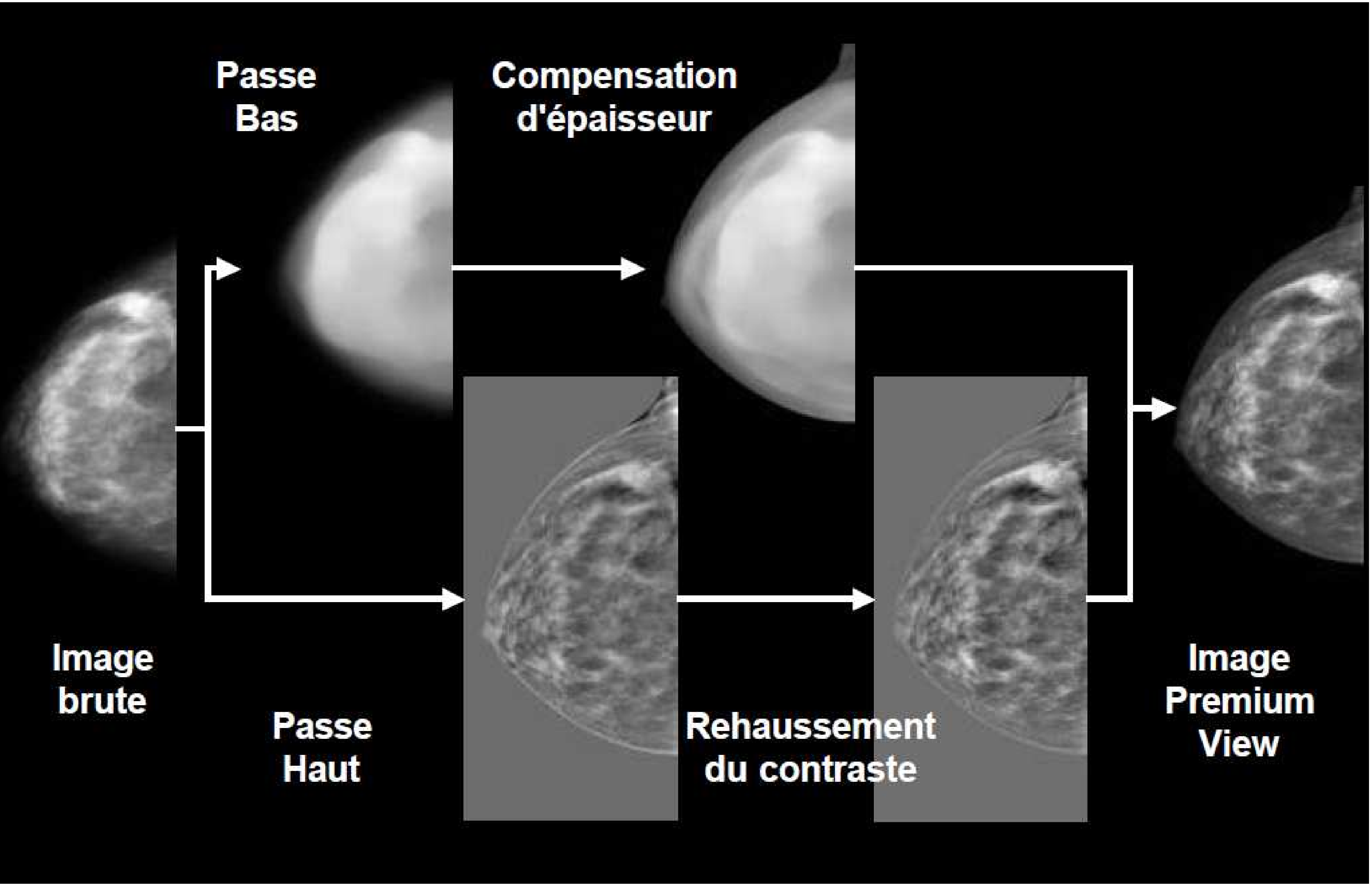
Thickness equalization



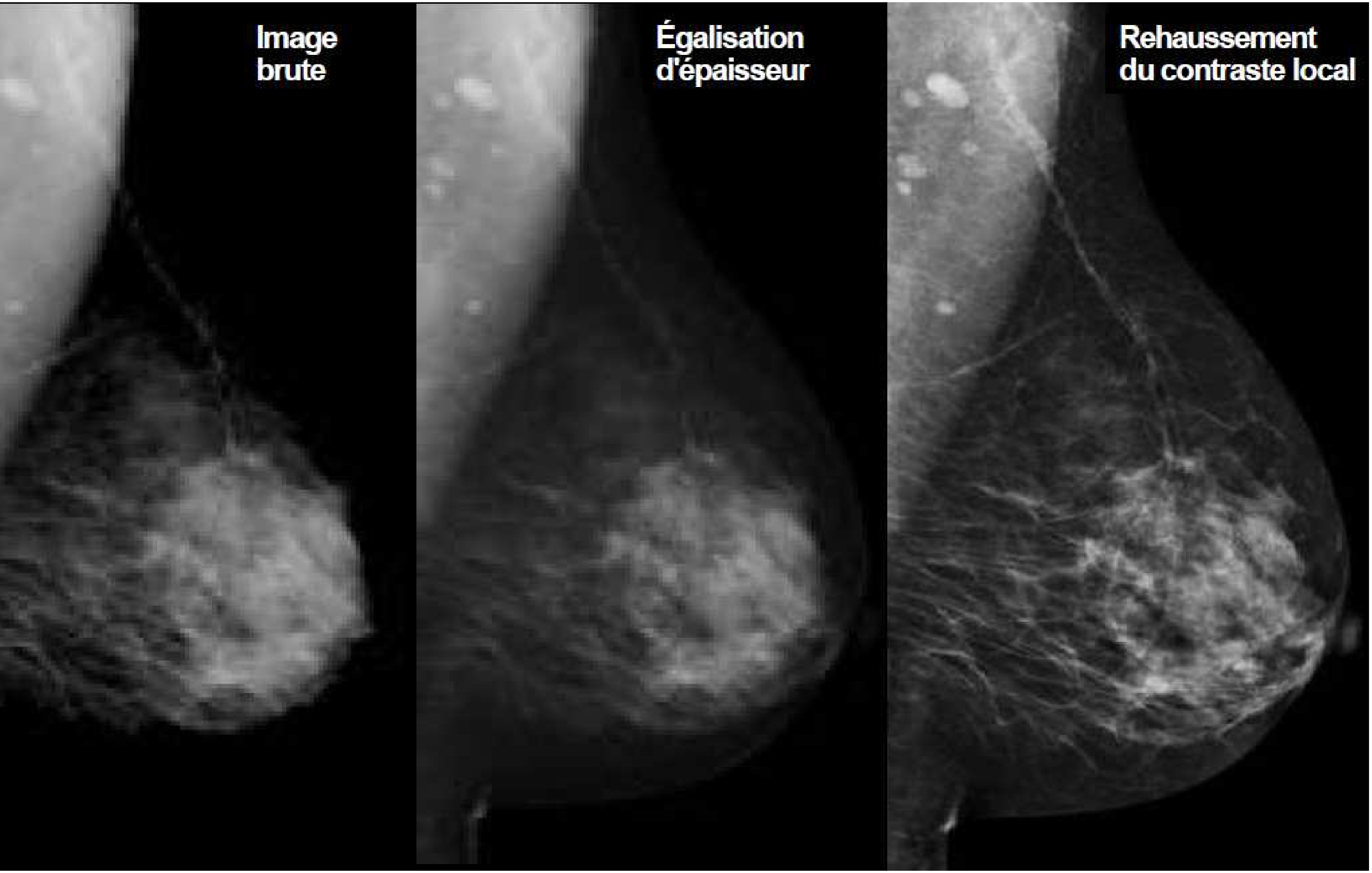
Contrast enhancement



Contrast enhancement

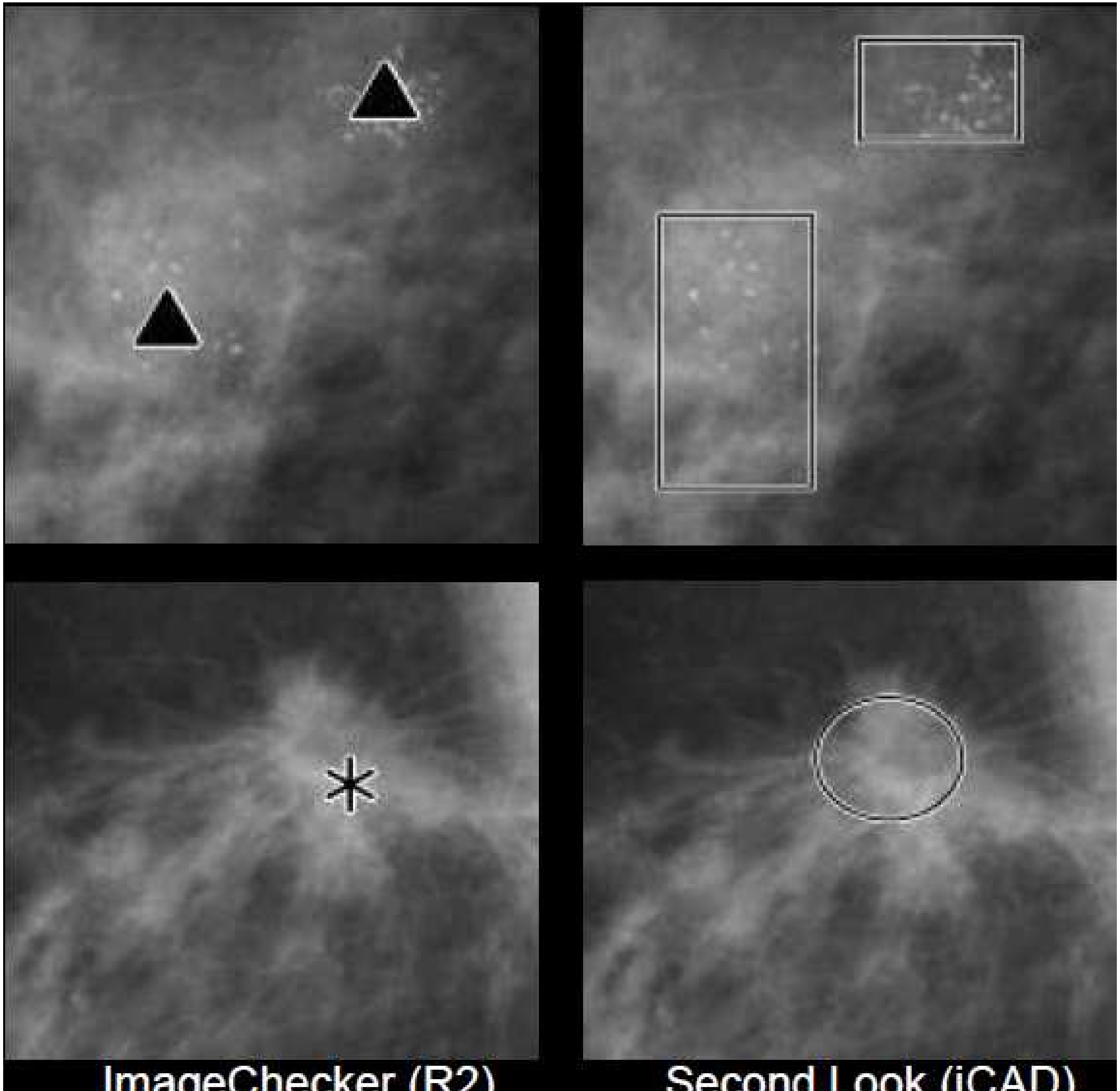


Contrast enhancement



Computer assisted detection: CAD

Computer assisted detection: CAD



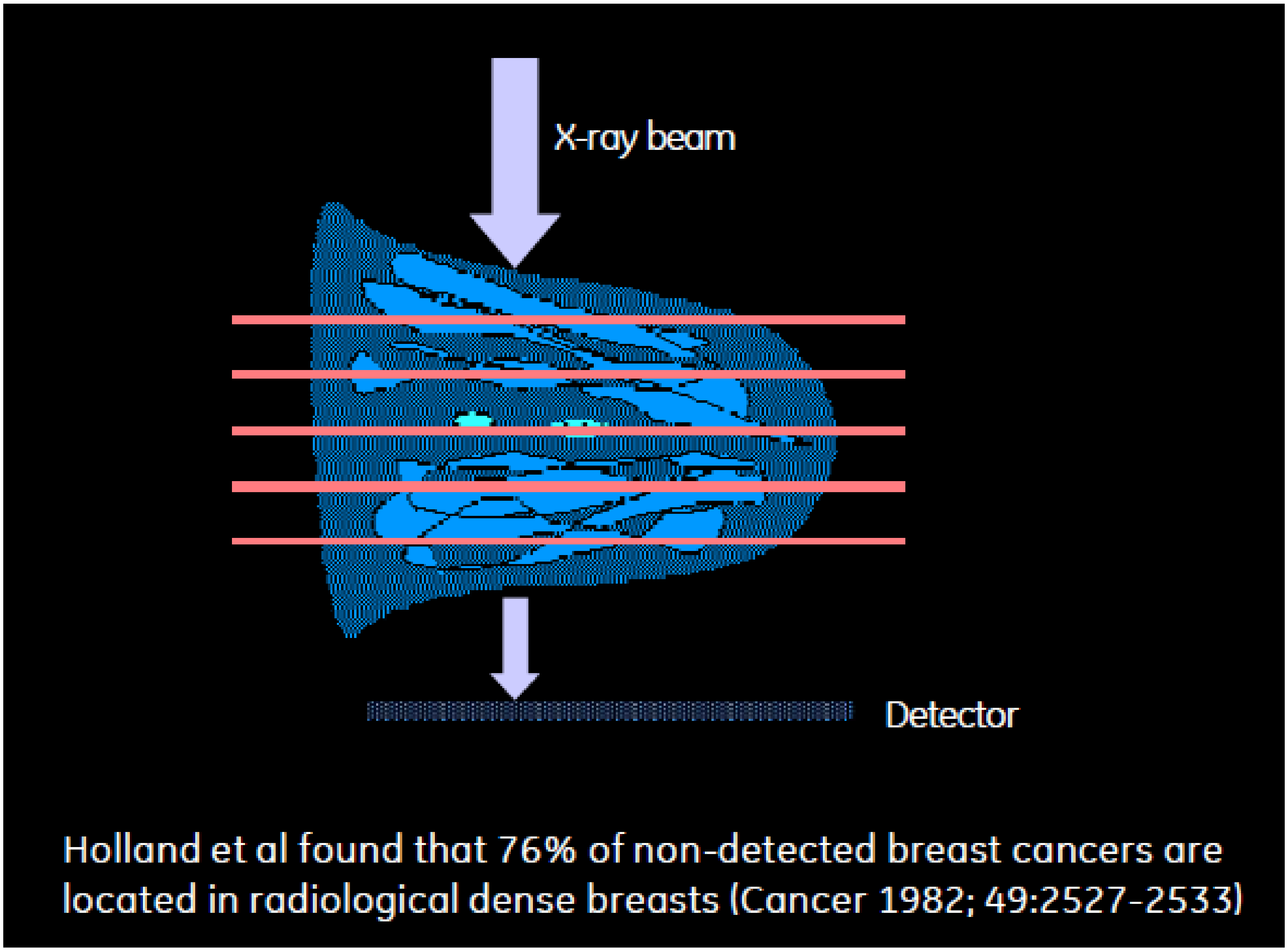
CAD methods

- Filtering and enhancement:
  - preferably using local methods
  - local statistics, wavelets...
  - compromise under-enhancement (can cause FN) / over-enhancement (FP)
- Segmentation:
  - thresholding and region growing
  - edge detection and deformable models
  - template matching
  - Markov random fields
  - left/right differences
  - multiscale
  - fuzzy methods
- Quantitative measures: intensity, shape, texture, clusters
- Classification:
  - artificial neural networks
  - kernel-based methods (SVM...)
  - decision trees

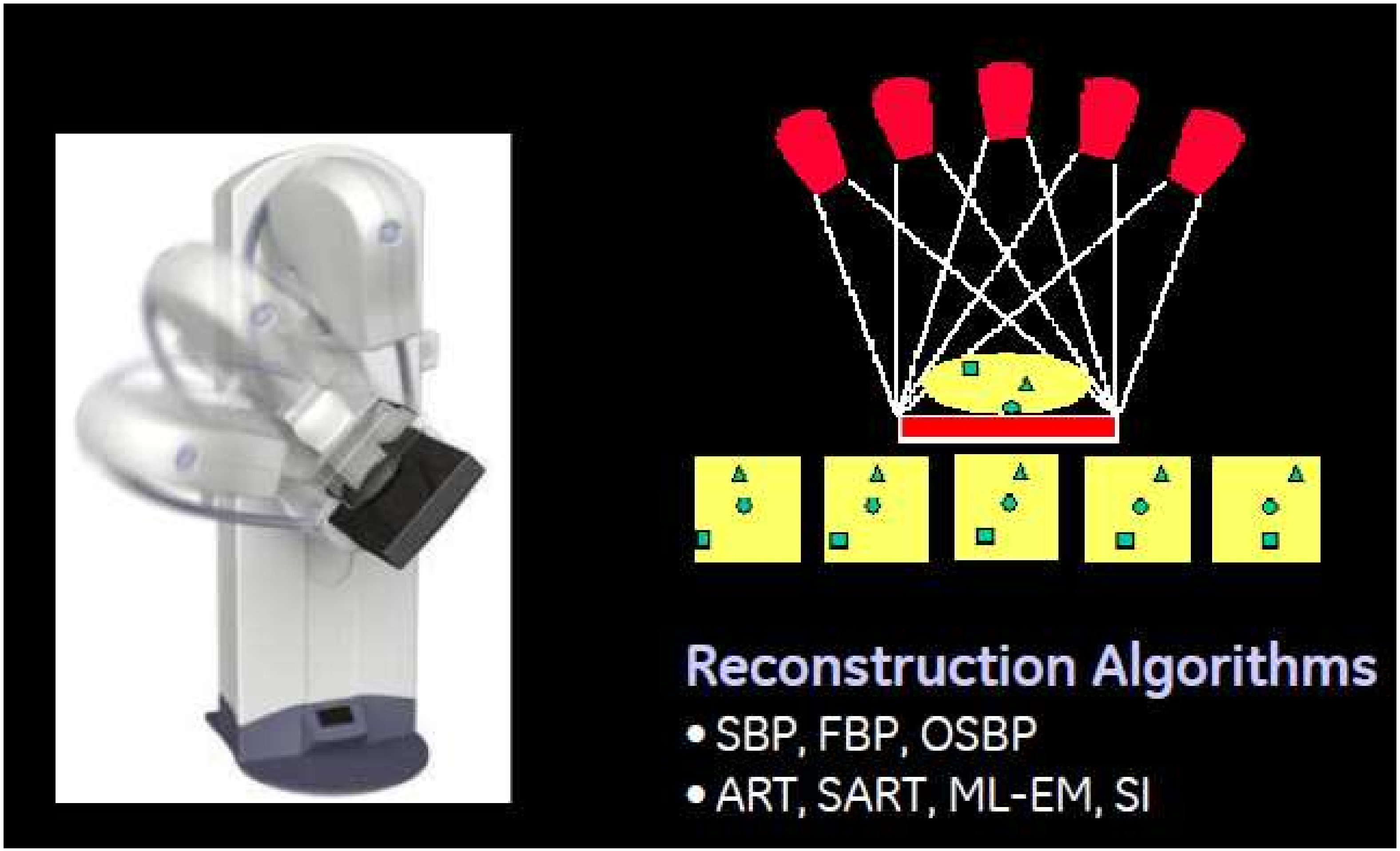
Evaluation:

- specificity and sensitivity
- ROC curve: true positives as a function of false positives

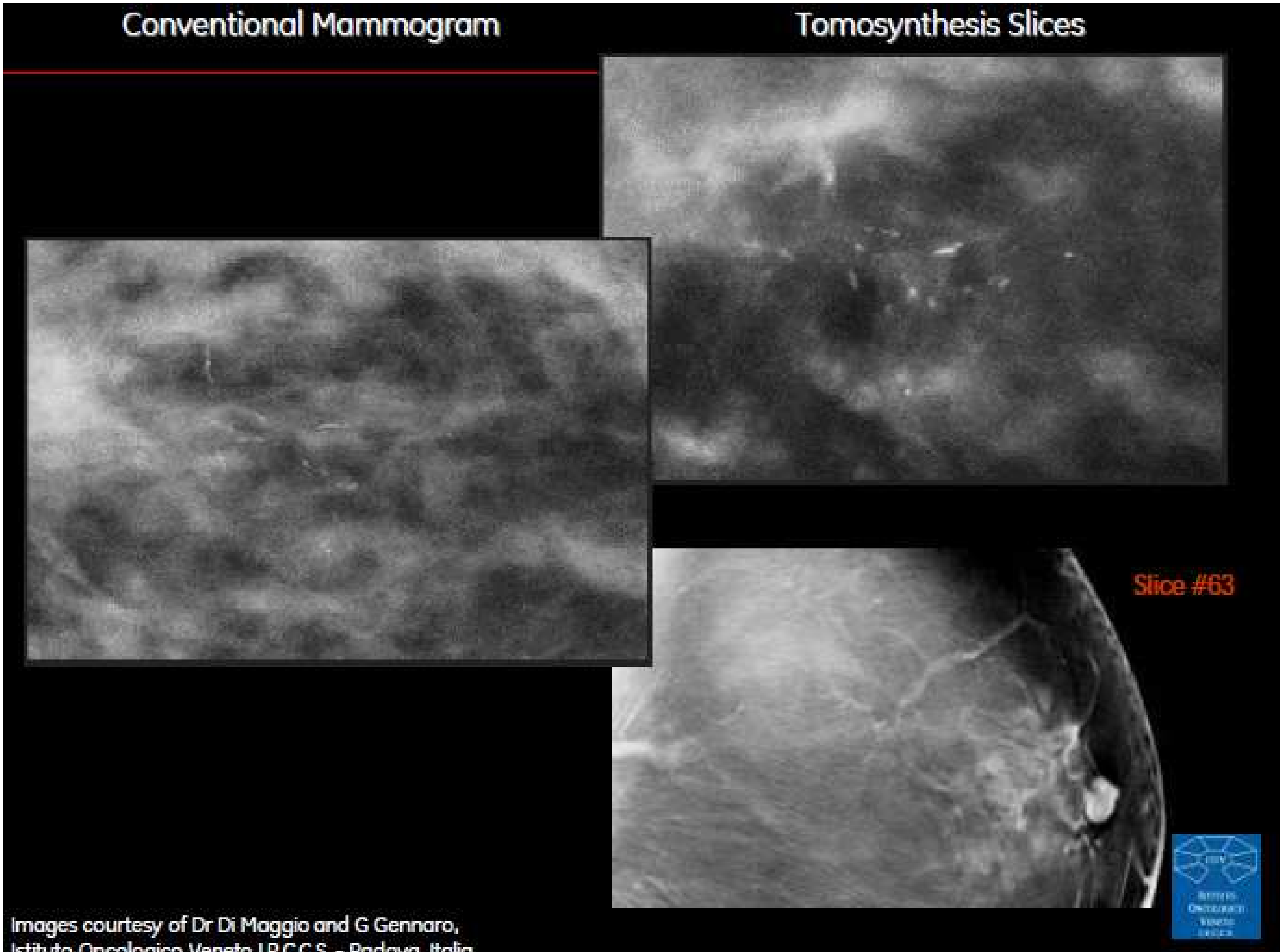
Tomosynthesis



Tomosynthesis



Tomosynthesis

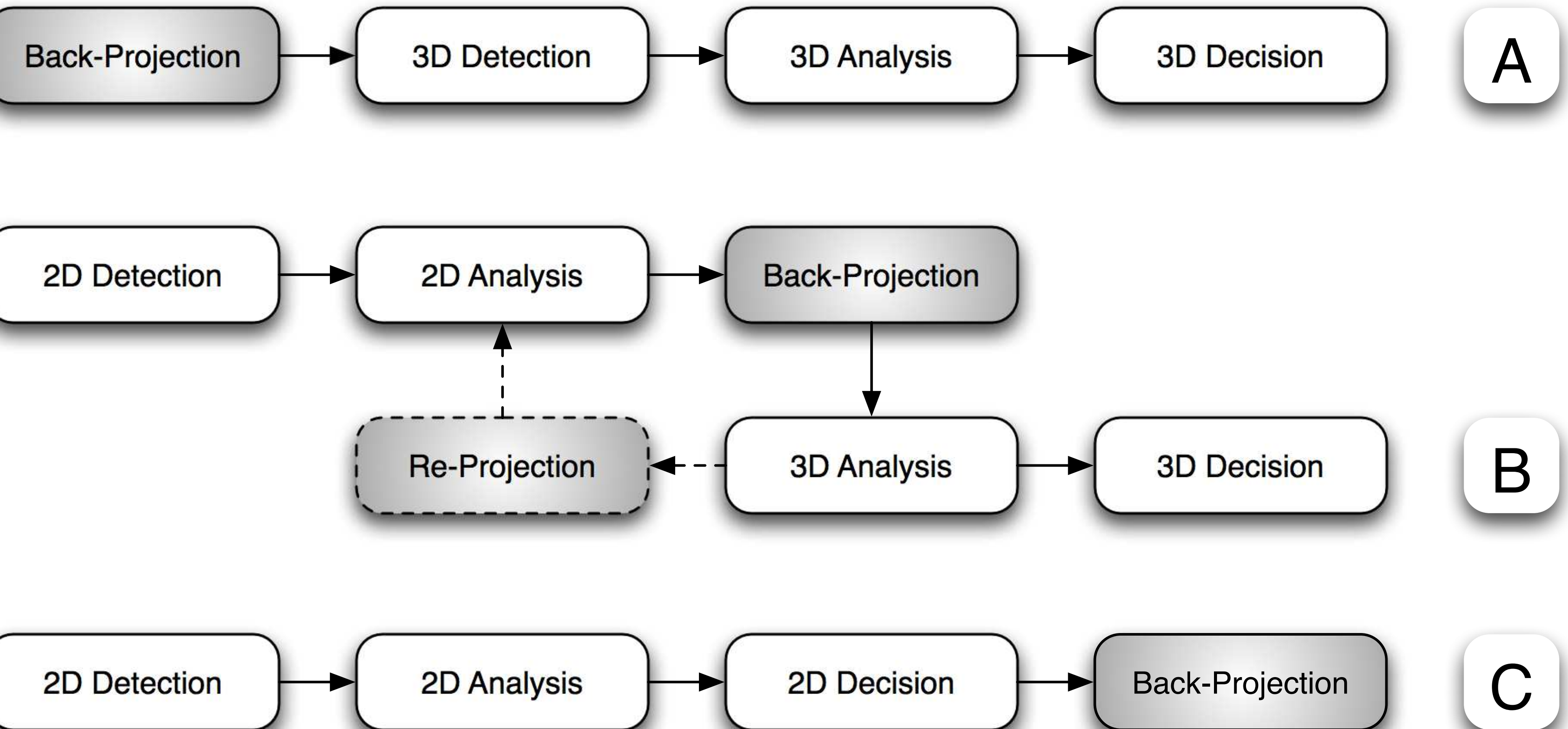


Tomosynthesis

- Greater conspicuity of lesions.
- Borders of lesions more clearly defined.
- Reduced call-back rate - almost eliminates recall for superimposed structures (summation shadows).
- Accurate 3-D location.
- Better differentiates benign from malignant.

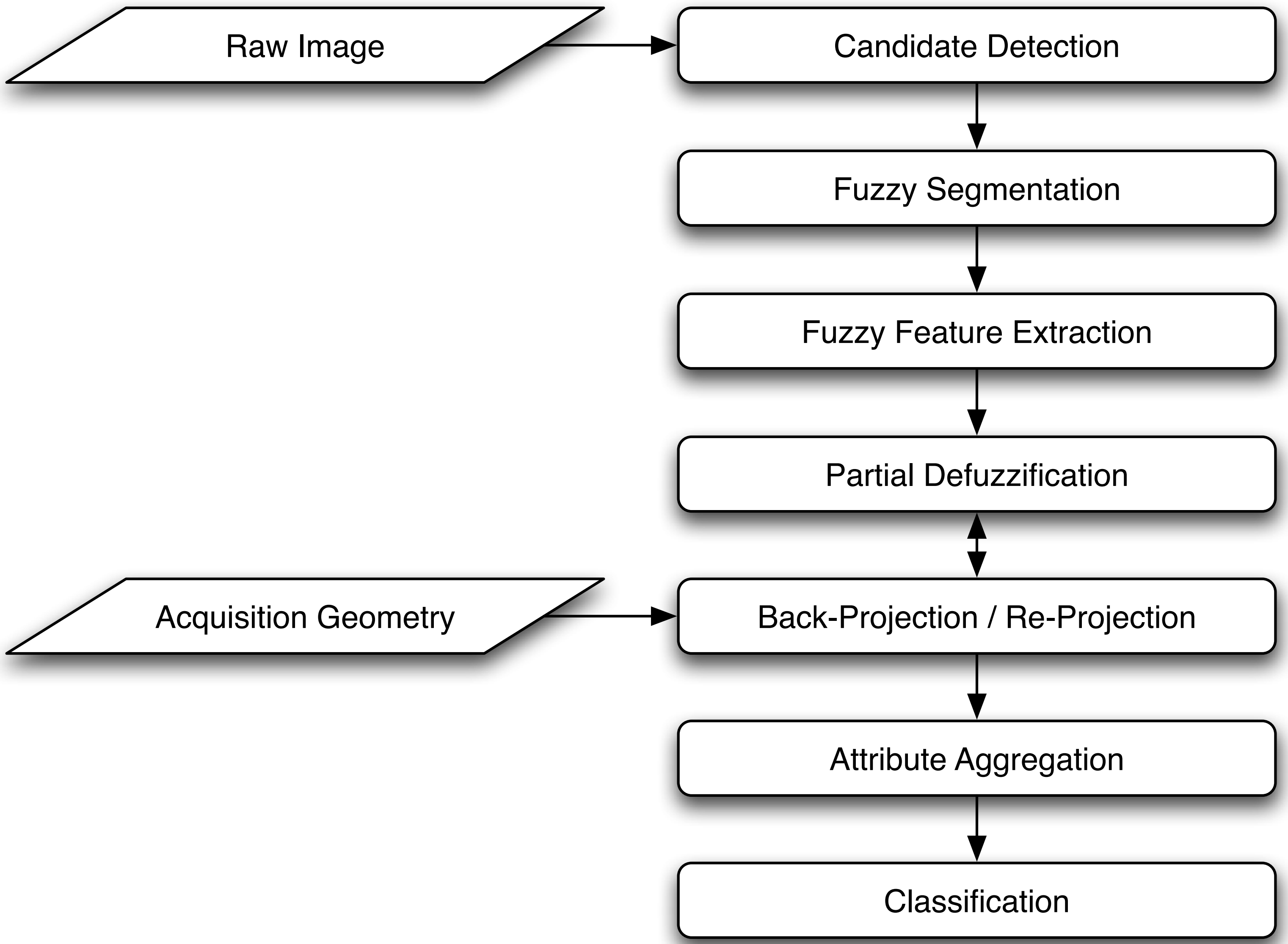
CAD for tomosynthesis

PhD thesis of G. Peters, with GE Healthcare



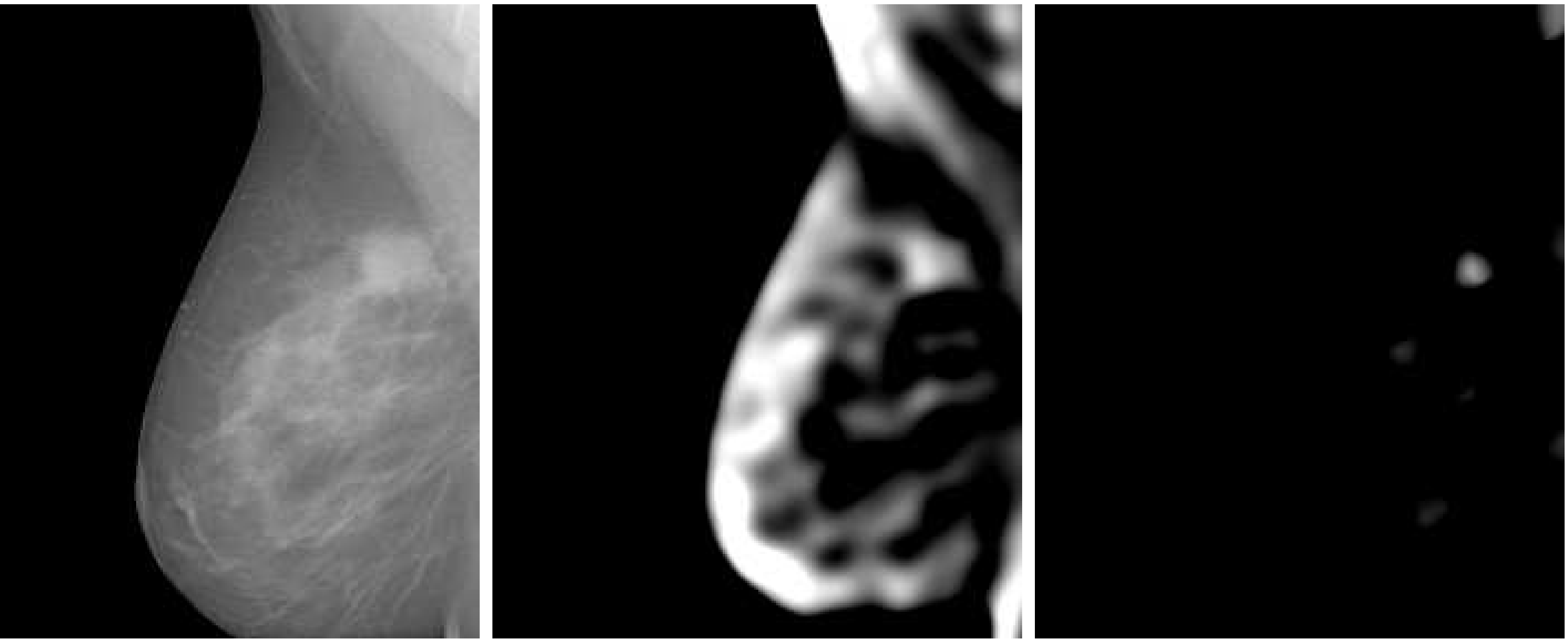
Choice: Strategy B

Algorithm scheme

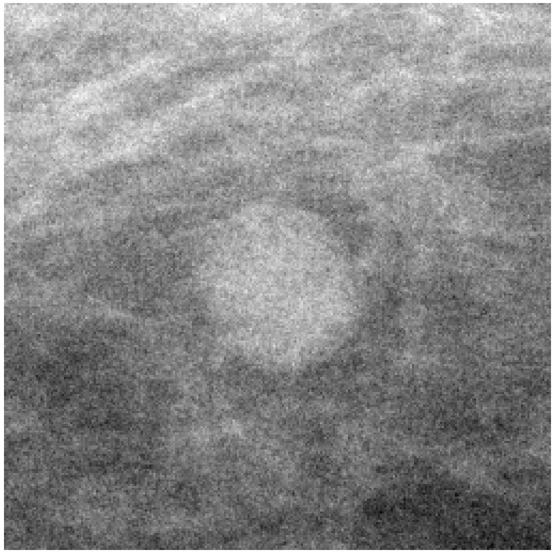


Dense kernel detector

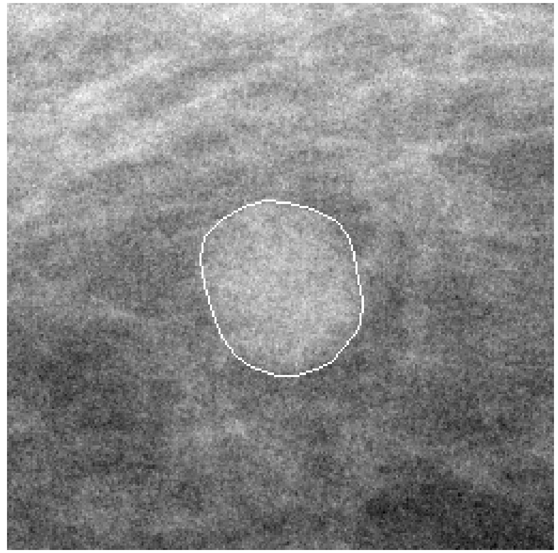
Using wavelets and brackground density estimation:



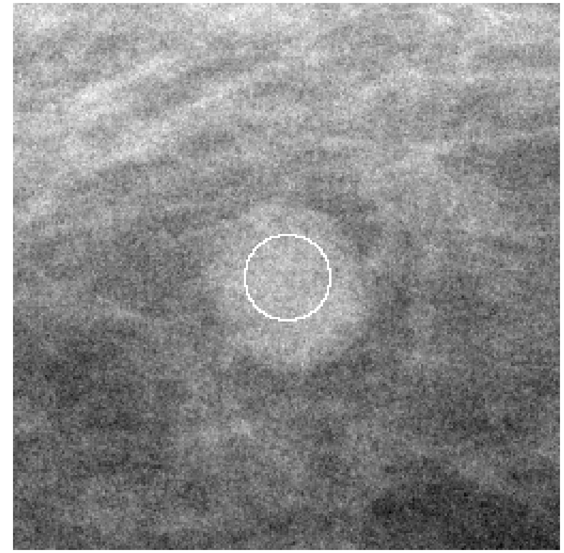
Segmentation result: circumscribed lesion



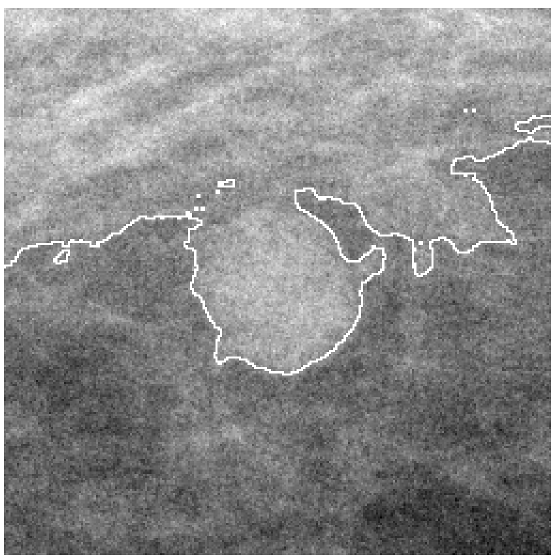
Original image



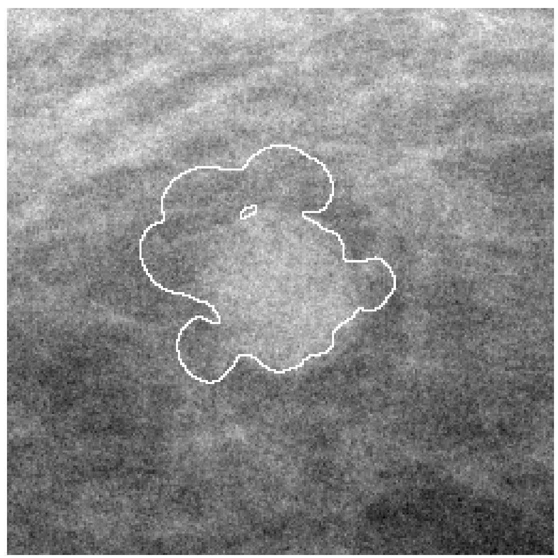
Reference contour



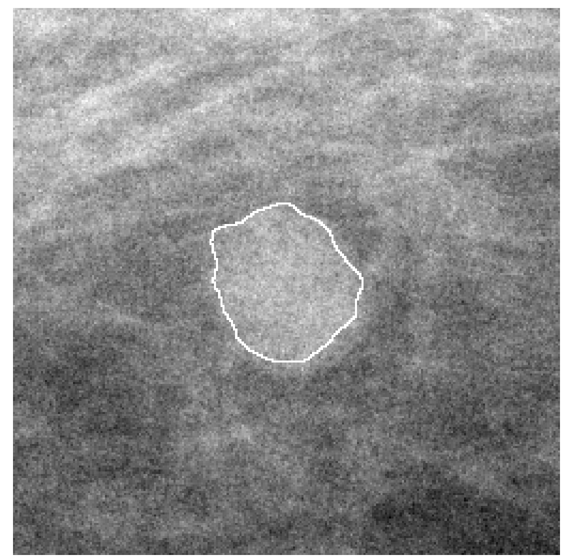
Initialization



Region-based

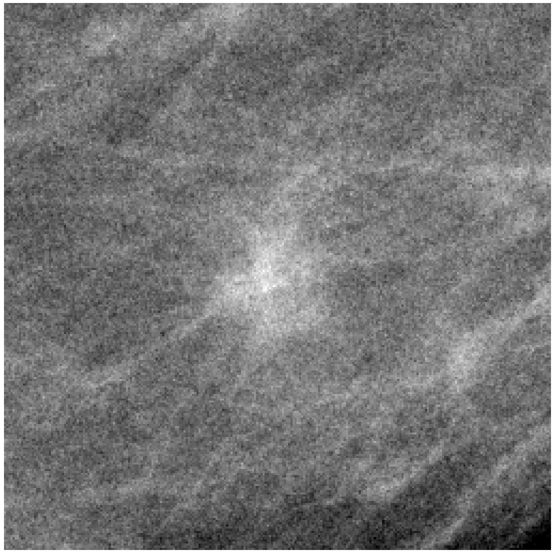


Contour-based

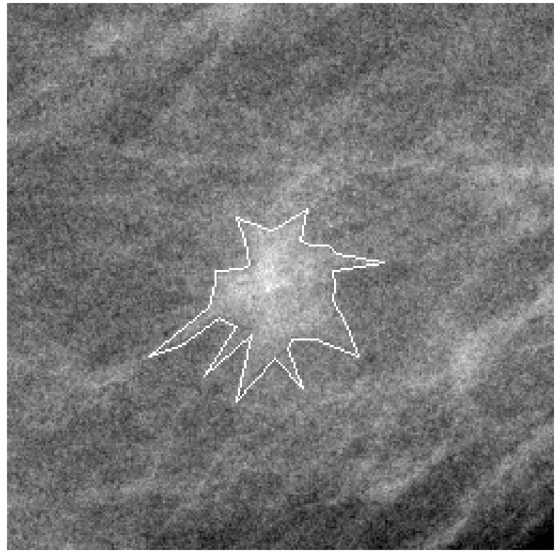


Hybrid

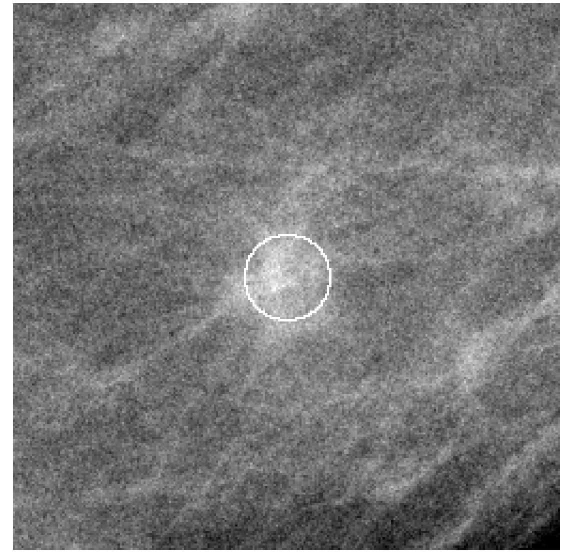
Segmentation result: spiculated lesion



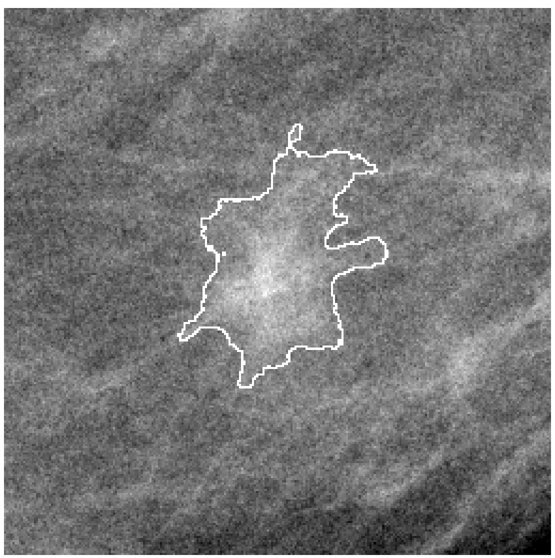
Original image



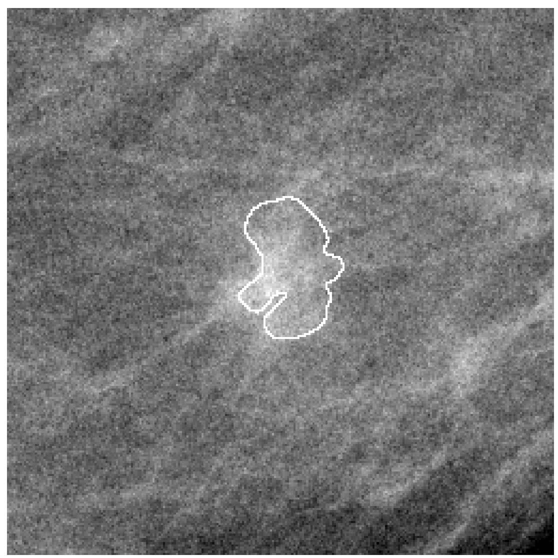
Reference contour



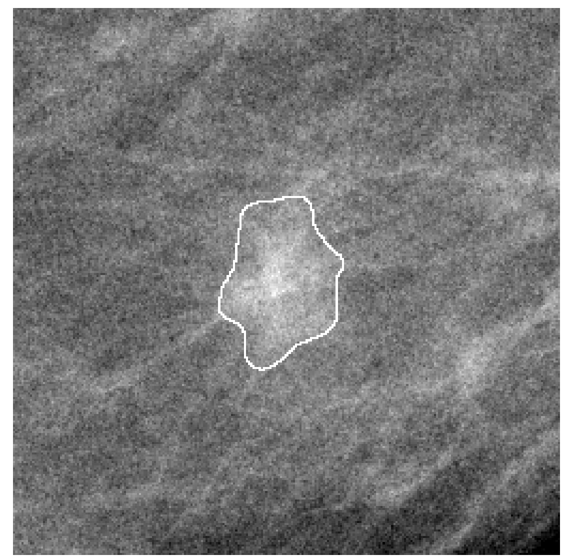
Initialization



Region-based

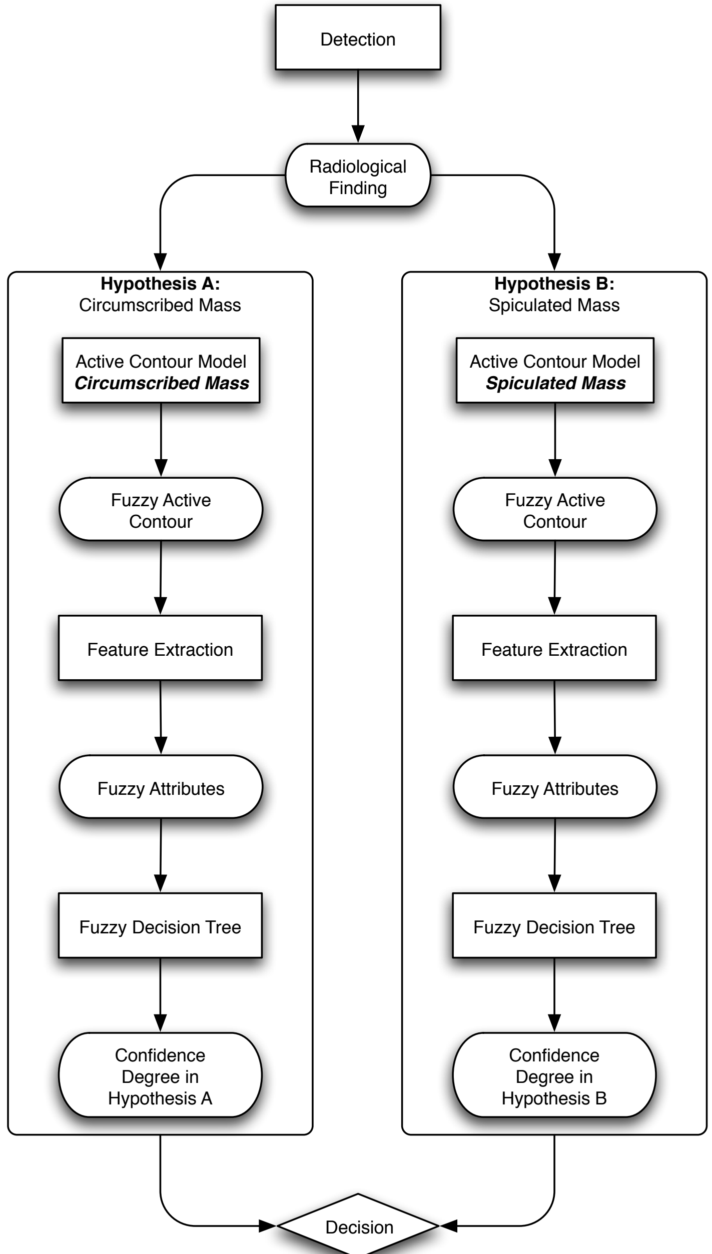


Contour-based

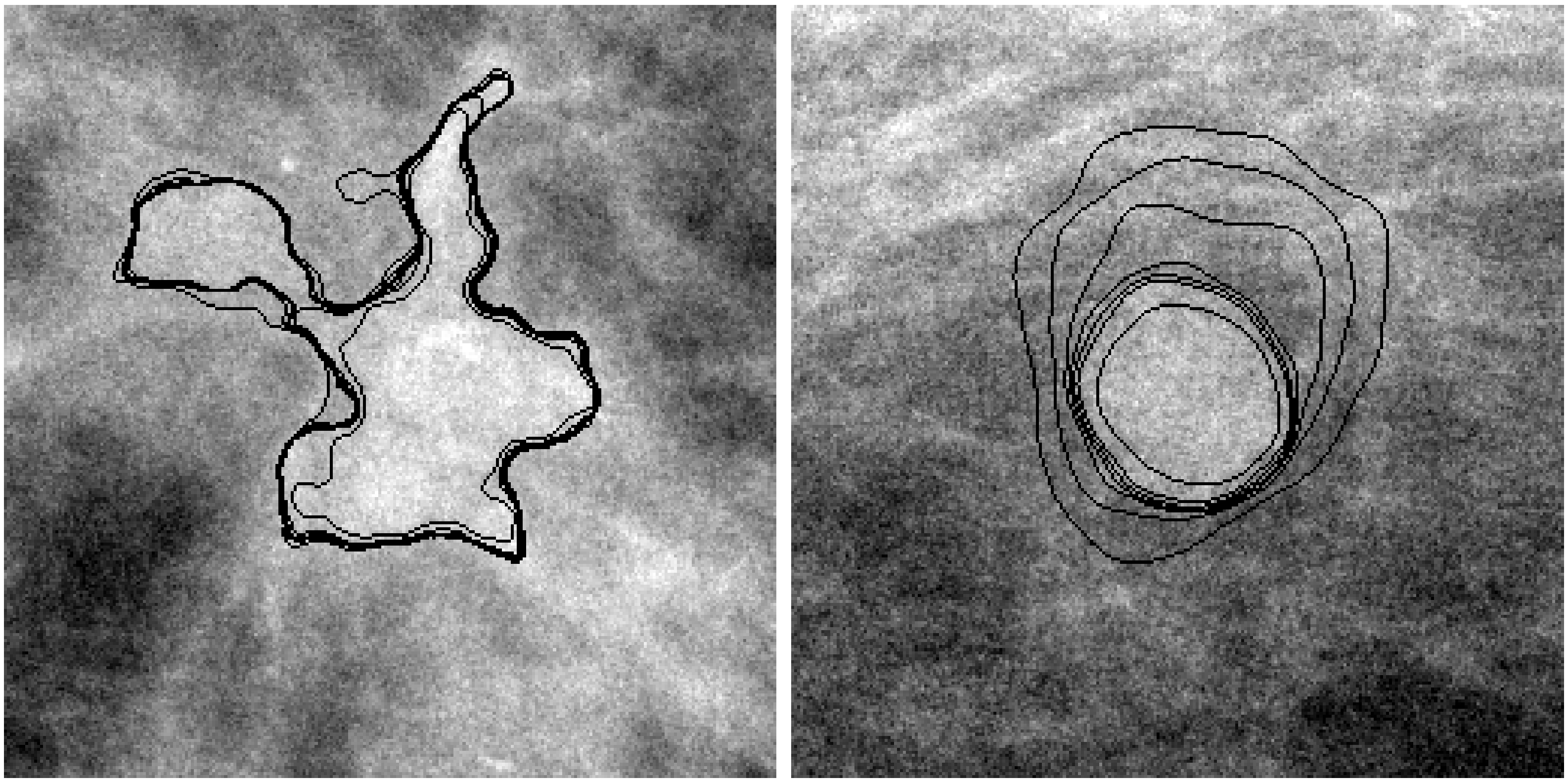


Hybrid

Hypothesis testing for a radiological finding

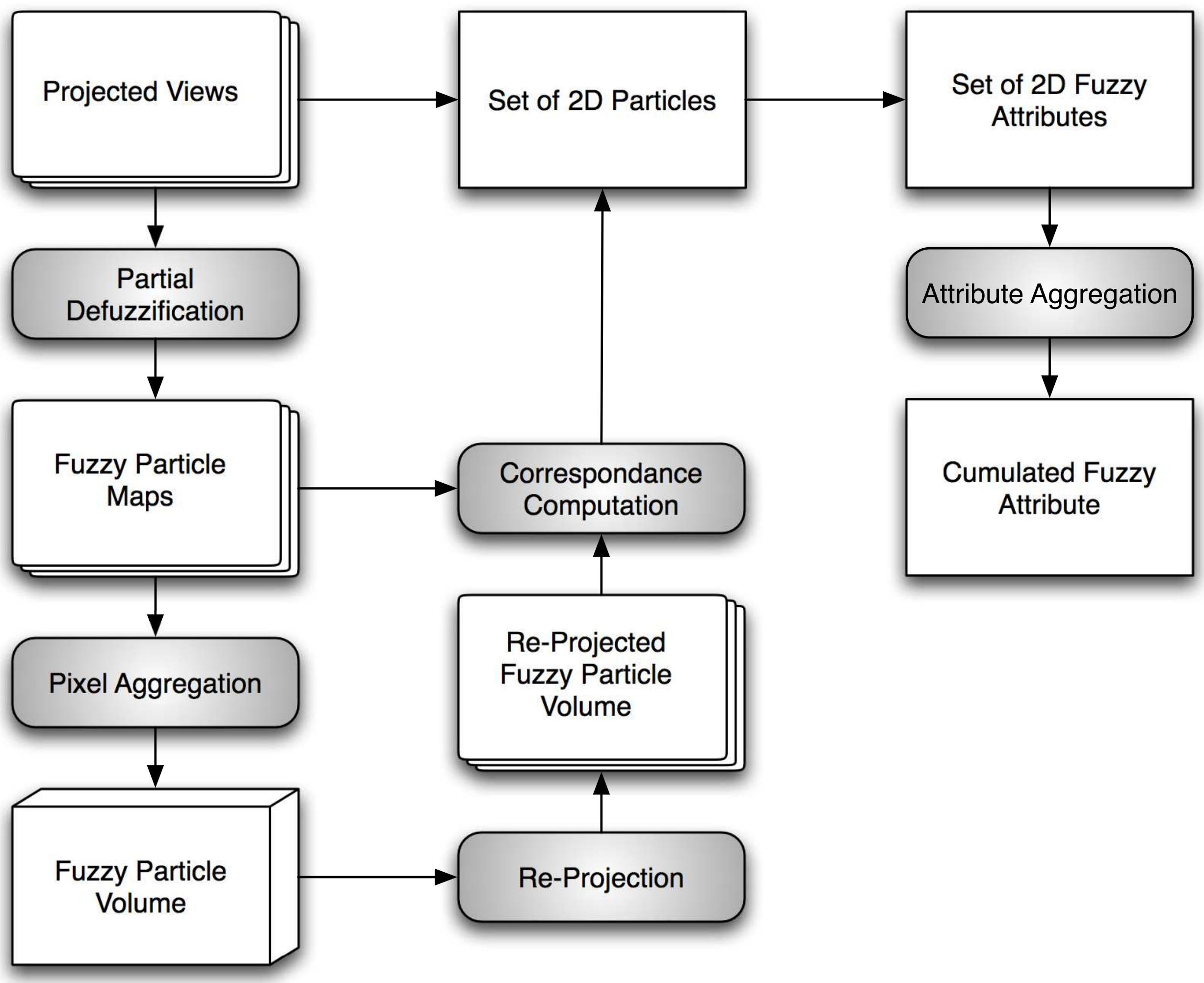


Features from fuzzy contours

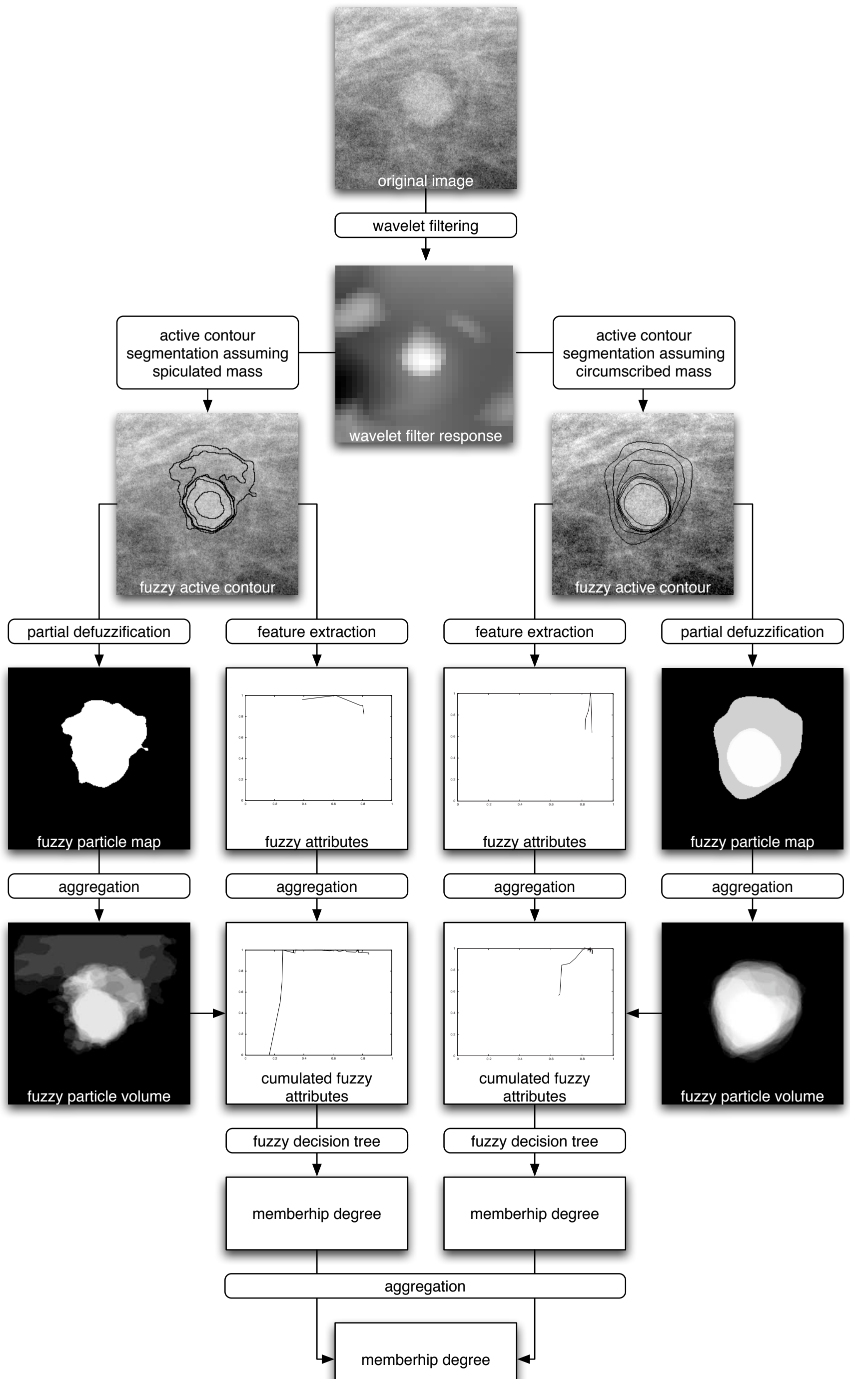


Features: area, compacicty, mean gradient along the contour, homogeneity...

Algorithm scheme for aggregation on particle level

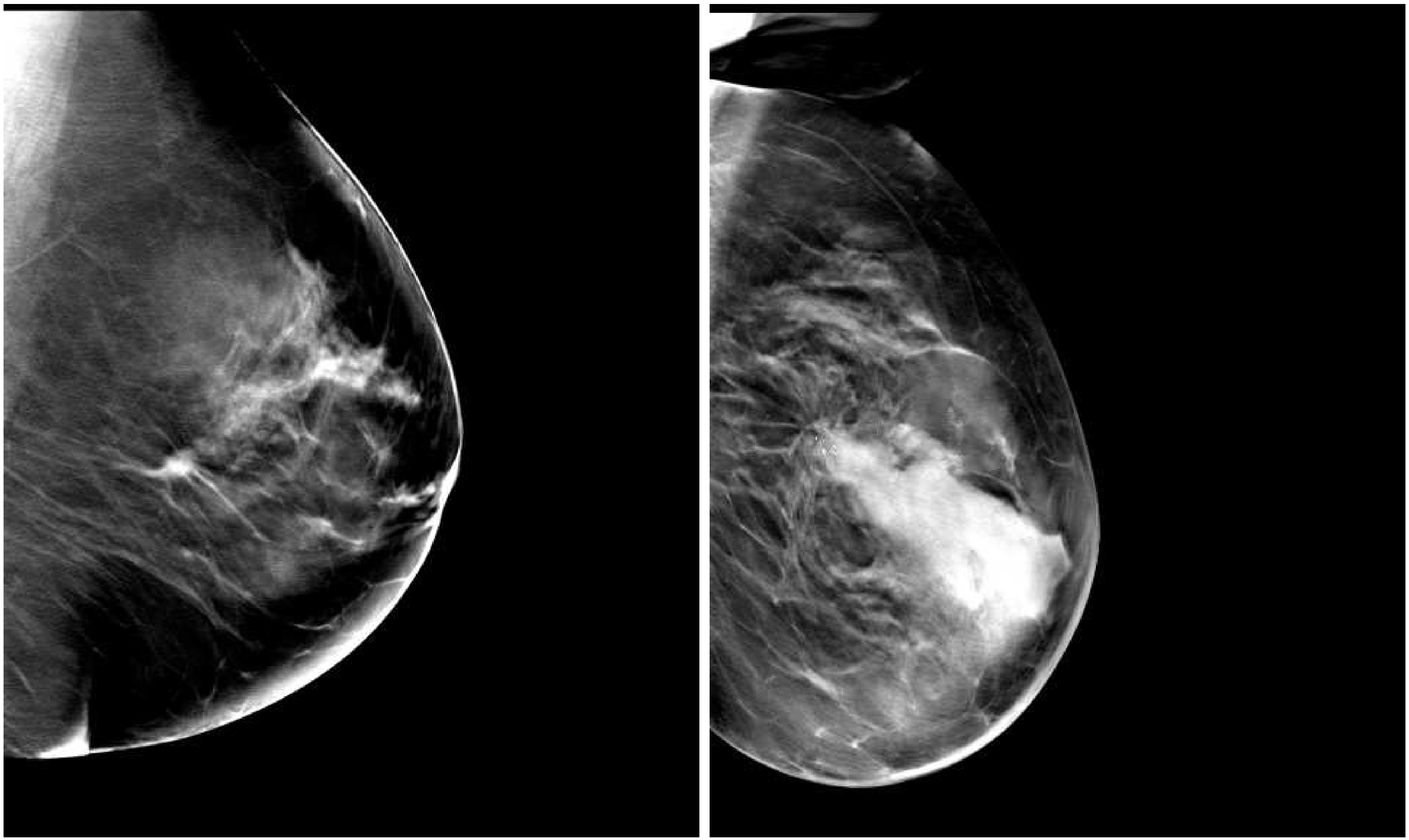


Complete processing chain

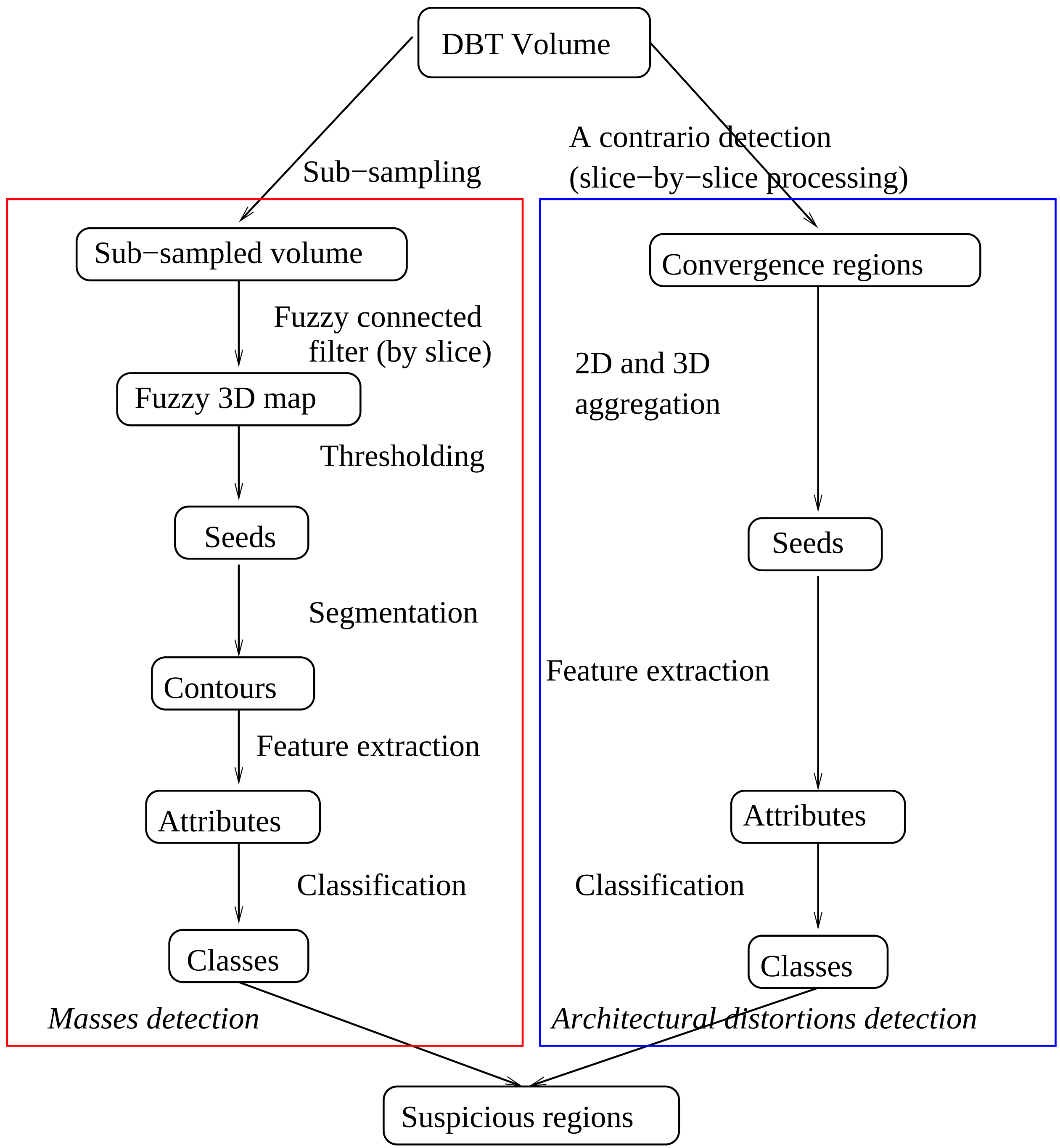


Automated detection of opacities and architectural distorsions in tomosynthesis

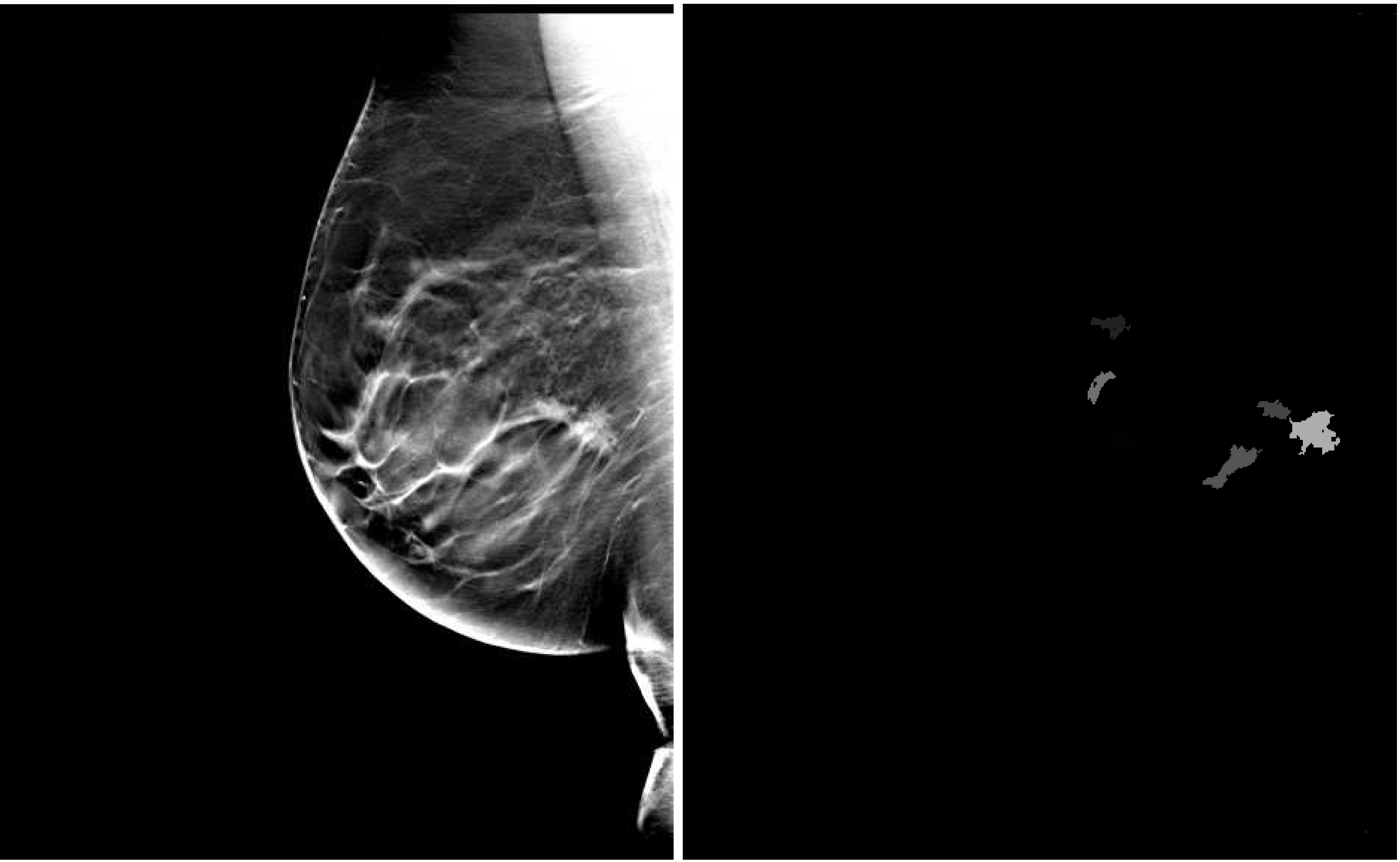
PhD thesis of G. Palma, with GE Healthcare



Global scheme: two "channels" approach



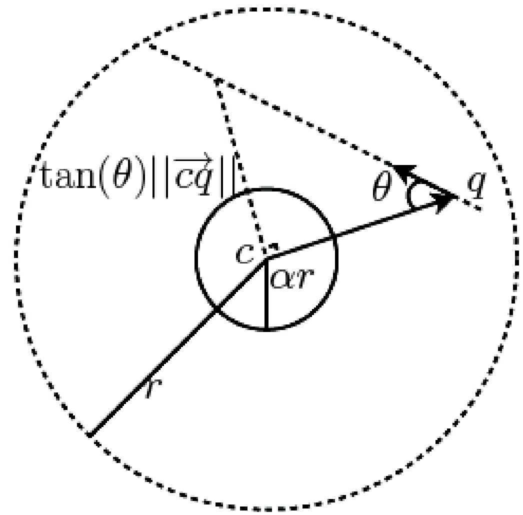
Makers from connected filters



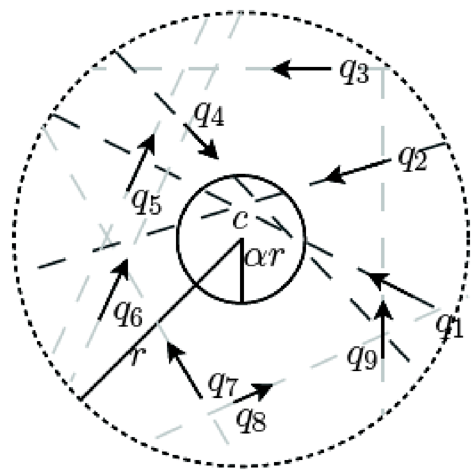
A contrario detection

$$K_{c,q,r} = \begin{cases} 1 \quad \textit{if} & (\alpha r < ||\overrightarrow{cq}|| < r) \\ & \wedge(\tan(\theta)||\overrightarrow{cq}|| \leq \alpha r) \\ 0 \ \textit{otherwise.} & \end{cases}$$

θ = angle between $\overrightarrow{cq}$ and orientation at point q.



$$Z_{c,r} = \sum_{q \in \Omega / \alpha r < ||\overrightarrow{cq}|| < r} K_{c,q,r}$$



A contrario detection

$Z_{c,r} \geq \lambda_r$ is ϵ-meaningful if the expectation of its number of occurrences in the image is less than ϵ (Desolneux et al., IJCV, 2000)

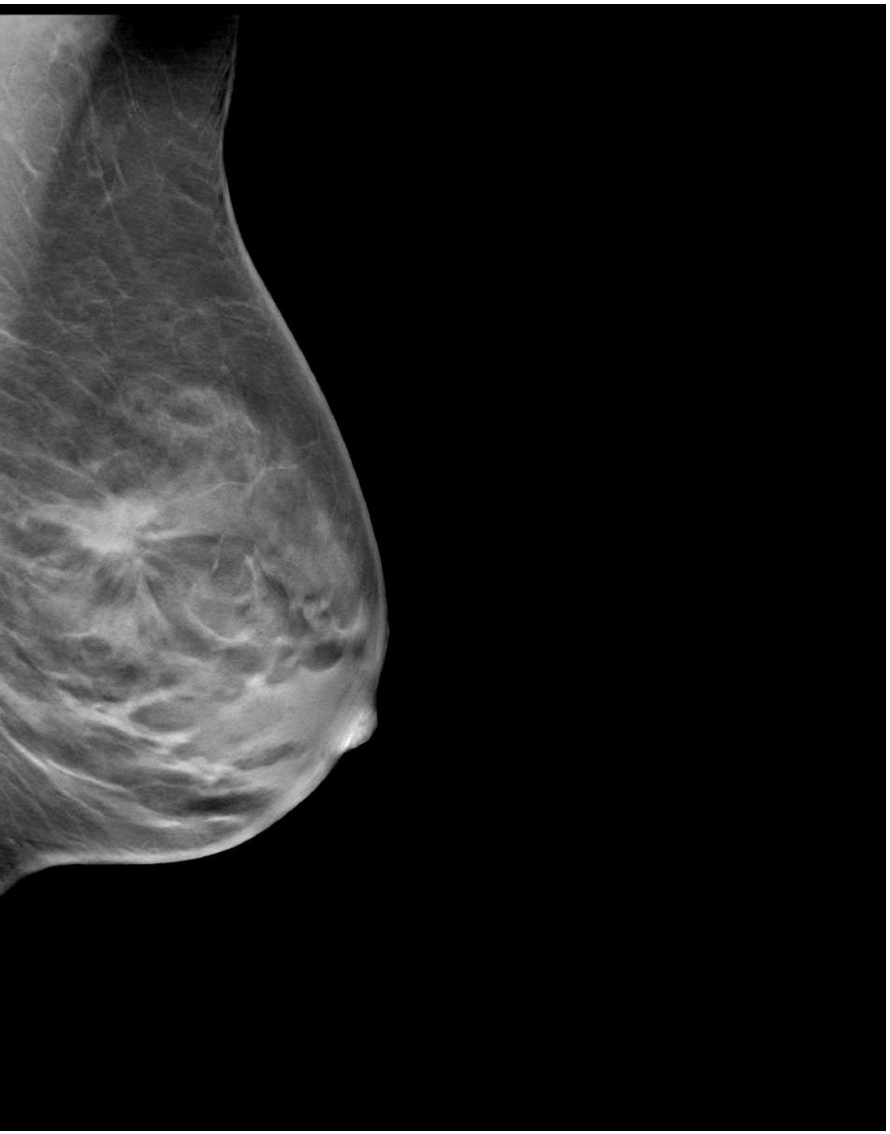
$$\lambda_r = \min \left\{ \lambda \in \mathbb{N} / P[Z_{c,r} \geq \lambda] \leq \frac{\epsilon}{M} \right\}$$

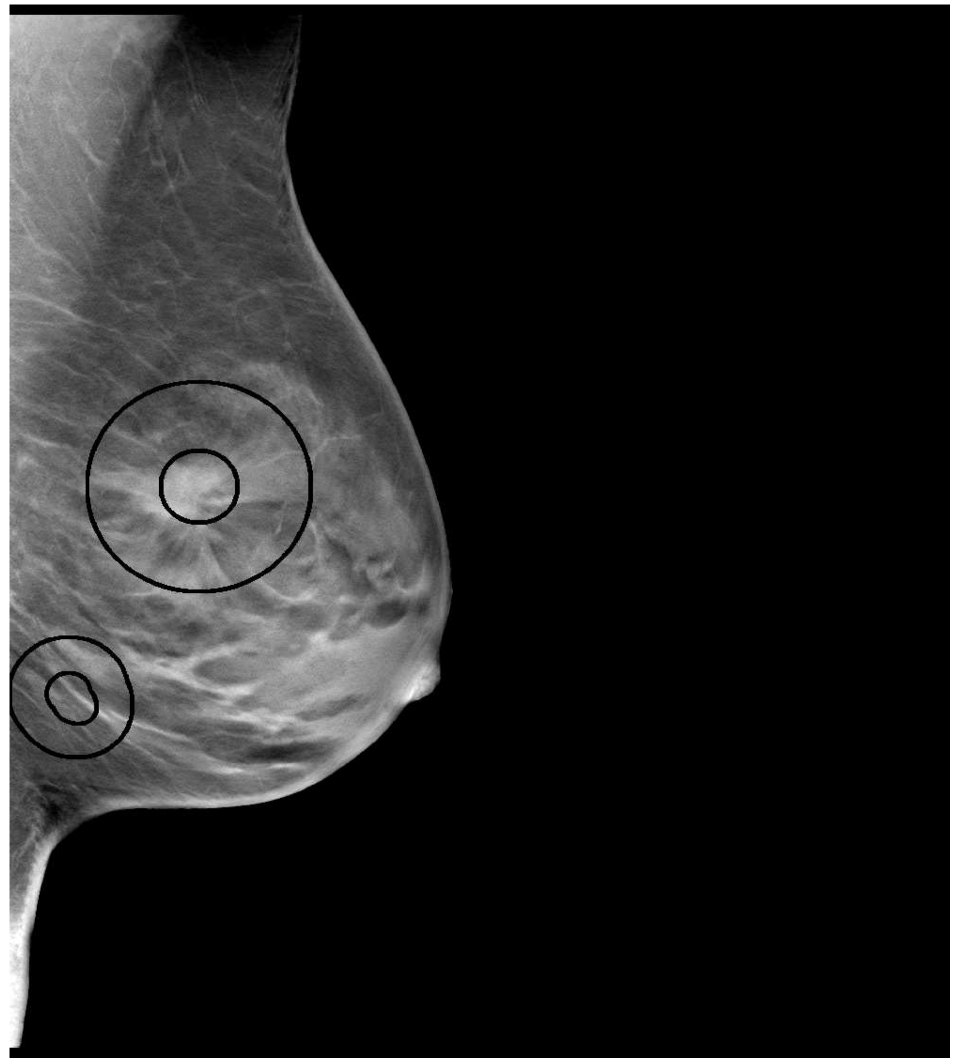
where M it the number of pairs (c, r) to be considered.

A contrario detection:

- computing $\{\lambda_r\}$,
- computing orientations,
- computing $Z_{c,r}$ for each (c, r),
- detection of ϵ-meaningful events ($Z_{c,r} > \lambda_r$).

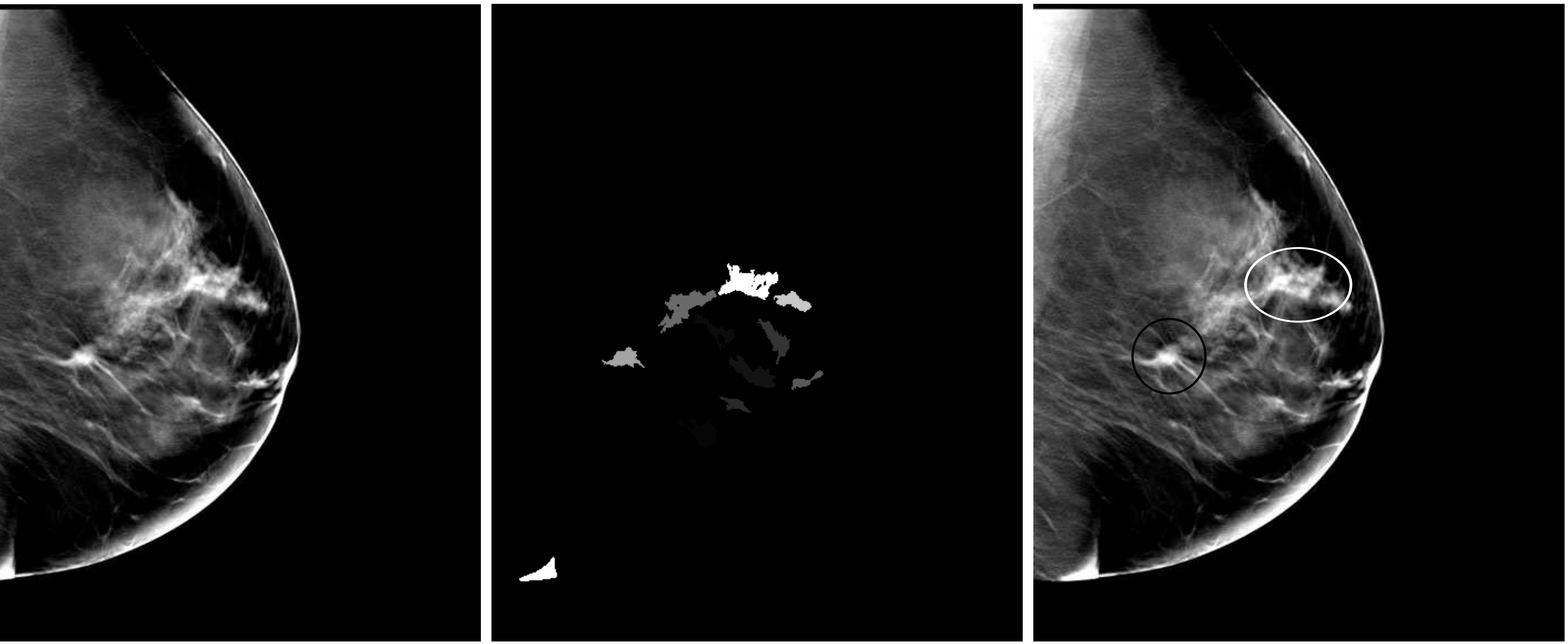
A contrario detection





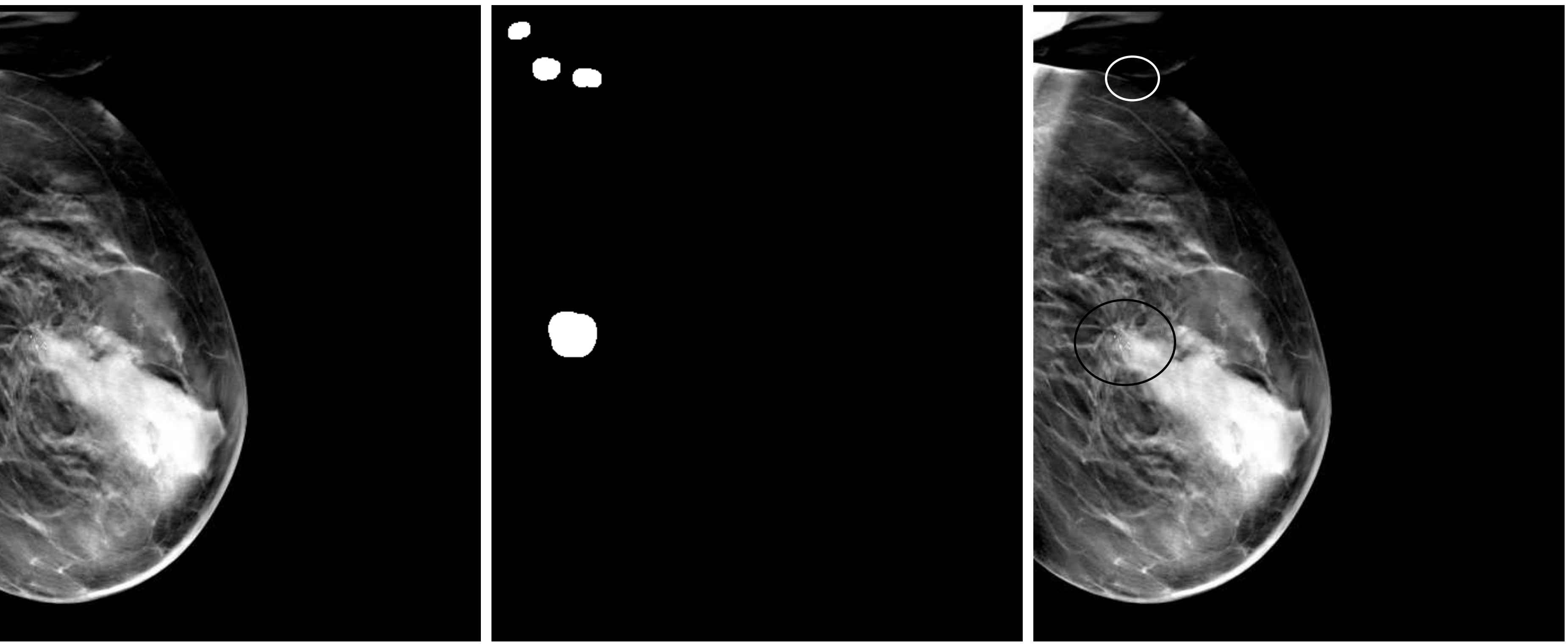
Results

Dense kernel detection:



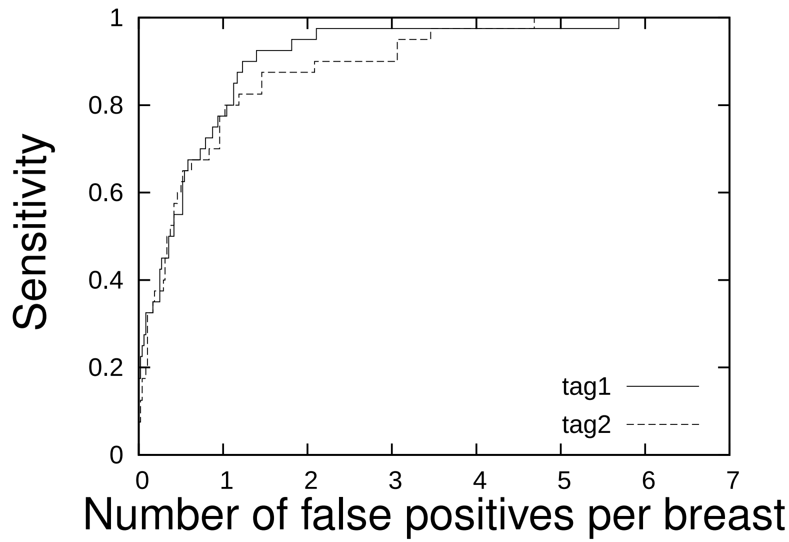
Results

Convergence detection:



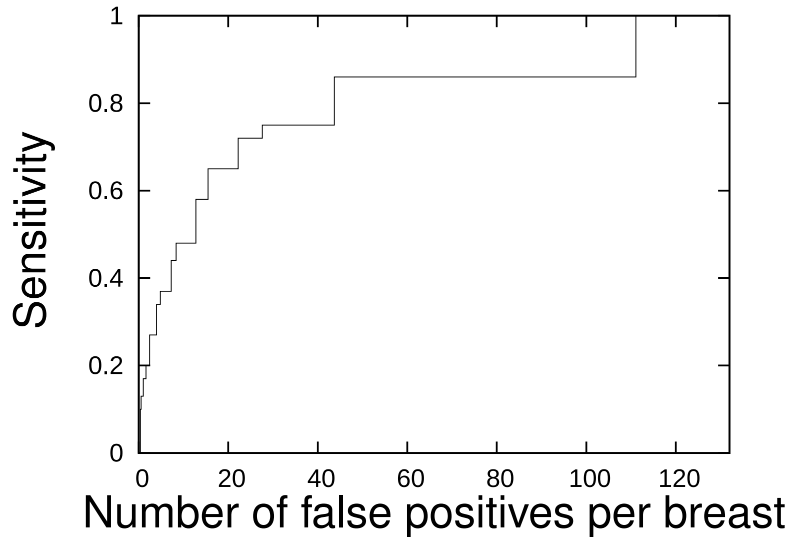
Performances

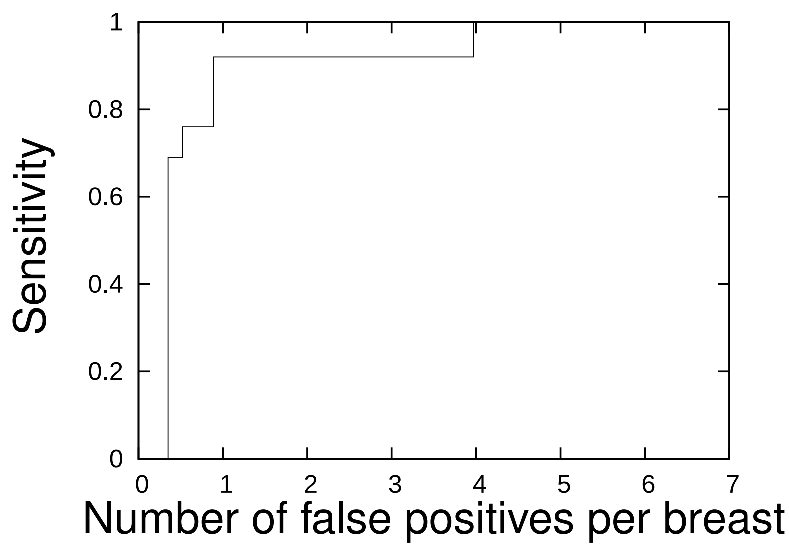
Performance of the whole dense kernel detection channel



Performances

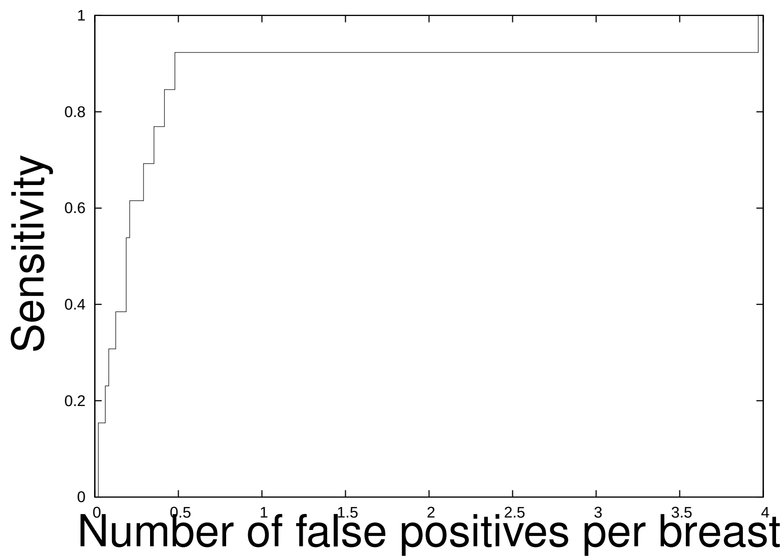
Performance of the *a contrario* detector for spiculated lesions only, and for architectural distortions and highly spiculated lesions





Performances

Performance of the suspicious convergence detection channel



Performances

Performance of the complete detection process, after the aggregation step

Sensitivity (%)	Specificity (# of false positives per breast)
81.13	1.31
90.57	1.60
96.23	1.81

Plane of a DBT volume exhibiting a strongly spiculated lesion, used in the convergence channel evaluation. Although this lesion is not detected by this channel, it is correctly detected by the dense kernel channel, and therefore by the final fusion step.