Diagnostic Enhancement of Screening Mammograms Based on Local Statistical Texture Models

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Seminar DAR, Liblice, December 2007

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Outline

Statistical Background of Mammographic Screening

Statistical Data of Breast Cancer:

- breast cancer happens to about 8% of women during their lifetime
- occurrence of malignant findings in screening mammograms is only about 1 to 3 of 1000
- 5 to 10% of findings is proposed for surgical verification by biopsy
- about 60 to 80% of biopsies result in benign diagnoses ($\Rightarrow$ unnecessary physical trauma and emotional stress)
- retrospective examinations report about 10 to 20% false negative results of screening mammogram evaluation
- total number of screening mammograms evaluated worldwide in one year may be of order of millions

Meaning of Mammographic Screening:

early detection of malignant abnormalities by mammographic screening is the only effective tool to decrease the breast cancer mortality rates

Local Statistical Model

local properties: square search window with cut-off corners ("patch")
$\mathbf{x} = (x_1, x_2, \ldots, x_N) \in \mathcal{X}, \quad \mathcal{X} = R^N$
$x_n \approx$ grey-levels of the window patch in a fixed order

Method:

approximation of the joint multivariate probability density of search window pixels by normal mixture of product components

local statistical model:

$$P(\mathbf{x}) = \sum_{m\in\mathcal{M}} w_m F(\mathbf{x}|\boldsymbol{\mu}_m, \boldsymbol{\sigma}_m) = \sum_{m\in\mathcal{M}} w_m \prod_{n\in\mathcal{N}} f_n(x_n|\mu_{mn}, \sigma_{mn})$$

$$f_n(x_n|\mu_{mn}, \sigma_{mn}) = \frac{1}{\sqrt{2\pi}\sigma_{mn}} \exp\{-\frac{(x_n-\mu_{mn})^2}{2\sigma_{mn}^2}\}$$

index sets: $\mathcal{M} = \{1, \ldots, M\}, \quad \mathcal{N} = \{1, \ldots, N\}$

Local Model Estimation

- **source database:** 2600 full mammograms of South Florida University http://marathon.csee.usf.edu/Mammography/Database.html
- four-view (full) digitalized mammogram: two medio-lateral and two cranio-caudal images
- **local statistical model** is estimated from a single mammogram
- $\Rightarrow$ each mammogram is evaluated individually
- $\Rightarrow$ the method need not be trained by other images
- $\Rightarrow$ it is not confronted with high natural variability of mammograms
- mirror transform is applied to right-hand-side images to utilize the underlying symmetry
- **patch:** square window of size 13 x 13 pixels with cut-off corners, dimension of $\mathbf{x}$ is $N = 145$ $(= 169 - 4 \times 6)$
- $M = 36$ mixture components, randomly initialized parameters
- **data set:** $|\mathcal{S}| \approx 10^5 - 10^6$ obtained by scanning the image with the search window

Local Evaluation of Screening Mammogram

Aim of Log-Likelihood Evaluation:

to emphasize mammographic lesions as “untypical” locations of high “novelty” and facilitate diagnostic evaluation of screening mammograms

LOG-LIKELIHOOD IMAGE:

$\log P(\mathbf{x}) \approx$ measure of typicality of the window patch $\mathbf{x}$

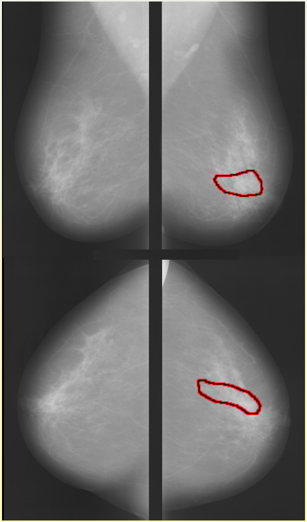
low values of $\log P(\mathbf{x})$ displayed as dark grey-levels should indicate less-probable “unusual” or “suspect” locations of mammogram

Properties of the Log-Likelihood Image:

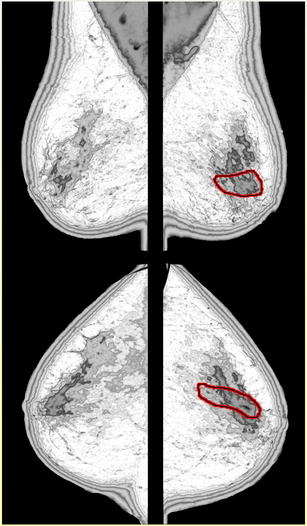
- “masses”: emphasized as dark regions with contour lines
- “micro-calcifications”: dark spots of the size and form of window
- useful for evaluation of contra-lateral findings and multifocal lesions

EXAMPLE 1: pleomorphic calcif., segmentally distributed

original C-0002-1

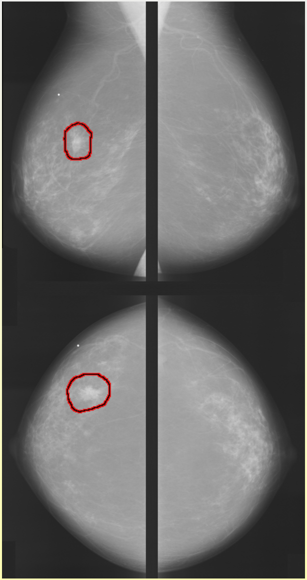


log-likelihood image

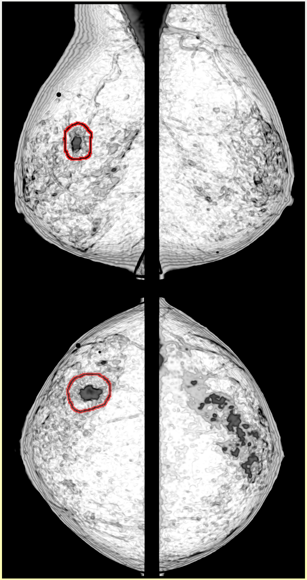


EXAMPLE 2: segmentally distributed calcification

original C-0016-1

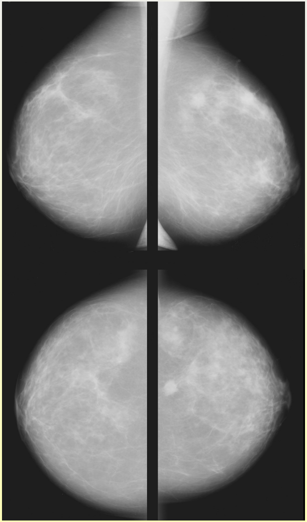


log-likelihood image

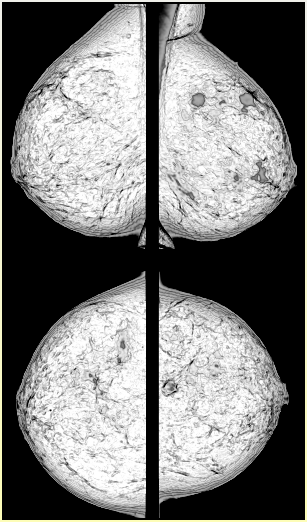


EXAMPLE 3: Mass, lobulated-architectural distortion

original B-3017-1

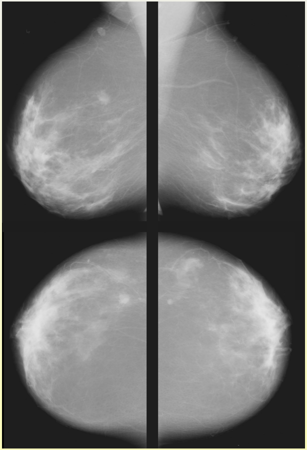


log-likelihood image

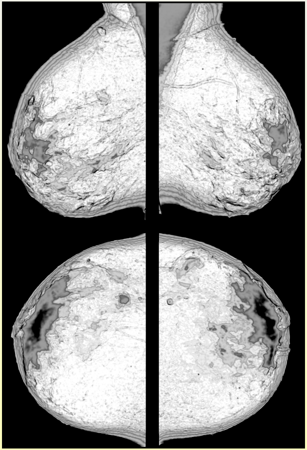


EXAMPLE 4: mass, lobulated shape, ill defined margins

original B-3020-1



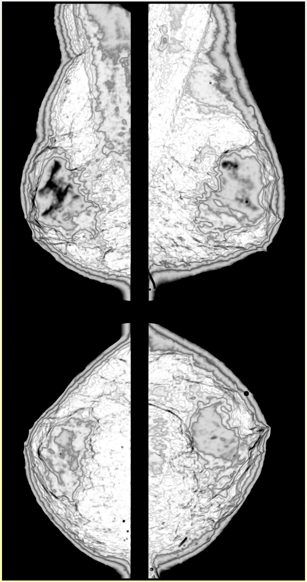
log-likelihood image



EXAMPLE 5: mass, focal-asymmetric density, margins n/a

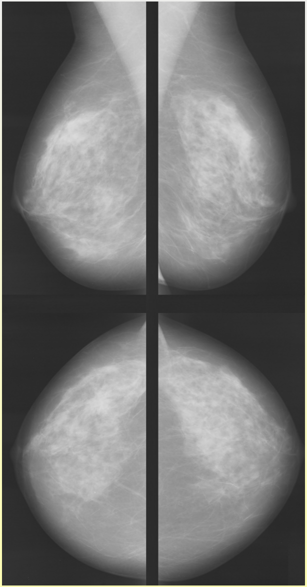
original B-3056-1

log-likelihood image

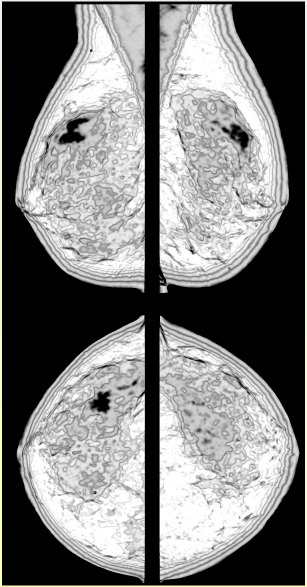


EXAMPLE 6: : mass, irregular shape, spiculated margins

original C-0001-1

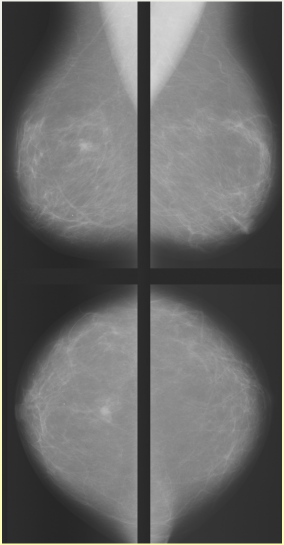


log-likelihood image

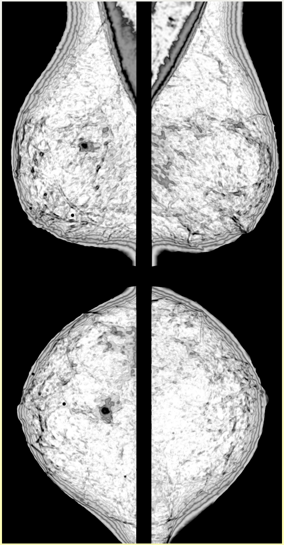


EXAMPLE 7: mass, irregular shape, ill-defined margins

original C-0143-1

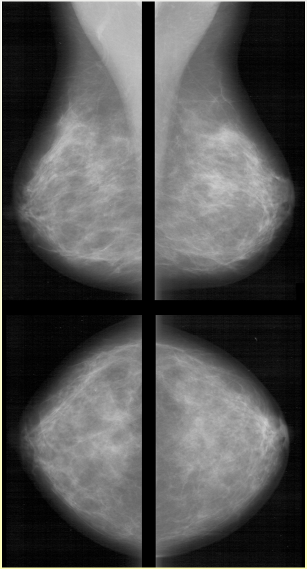


log-likelihood image

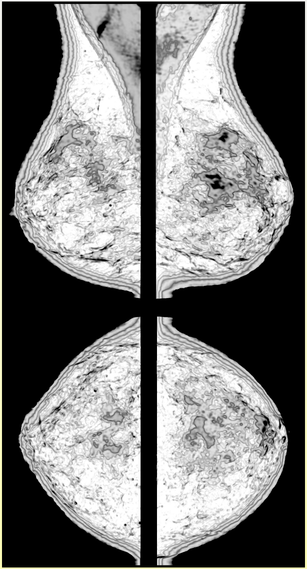


EXAMPLE 8: punctate calcification, clustered distribution

original D-4163-1

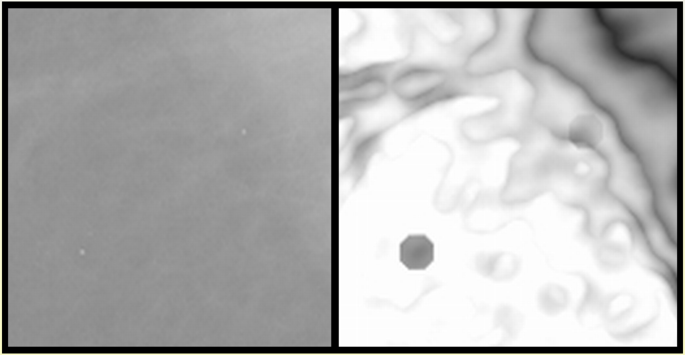


log-likelihood image



Identification of “Micro-Calcifications” by Spots

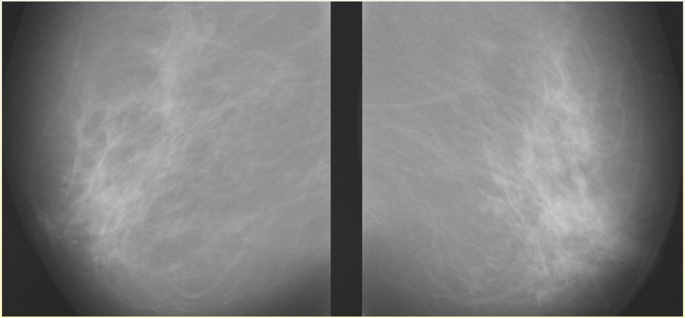
original micro-calcifications corresponding dark patches



Remark: Each position of the window containing a light pixel implies a lower value of $\log P(\mathbf{x})$. $\Rightarrow$ A light pixel is identified as a dark spot of window-size.

Identification of “Masses” by Contour-Lines

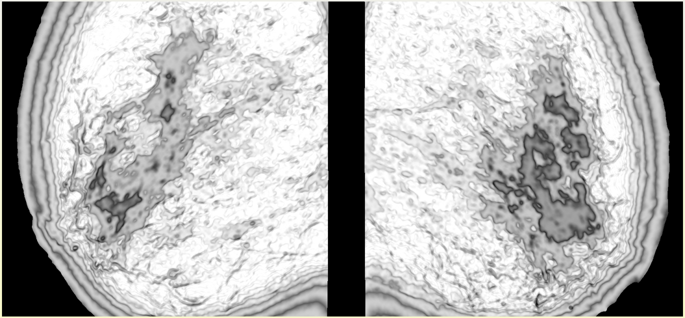
part of the screening mammogram containing suspect “masses”



Remark: The masses may be quite subtle, may have smooth boundaries and different shapes. Detection and classification of masses is more difficult than detection of micro-calcifications.

Identification of “Masses” by Contour-Lines

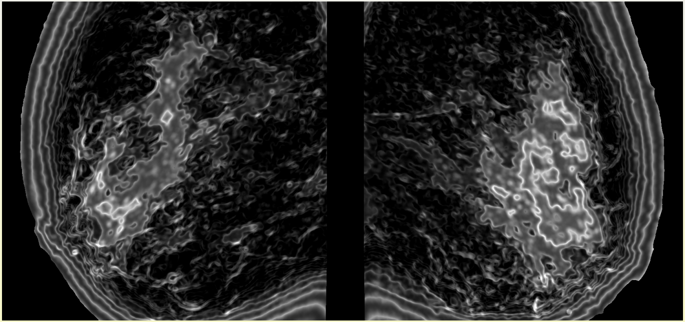
contour lines around “masses” and at the mammogram boundaries



Remark: Log-likelihood values $\log P(\mathbf{x})$ are typically dominated by a single component of the mixture which is most adequate to the underlying region. The “switching” of components at the boundaries of different regions accompanied by decreased log-likelihood values is responsible for the arising contour lines.

Identification of "Masses" by Contour-Lines

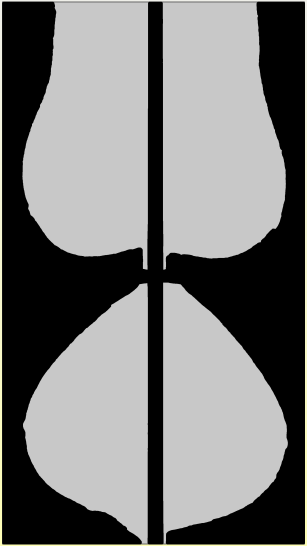
contour lines displayed by the inverse log-likelihood image



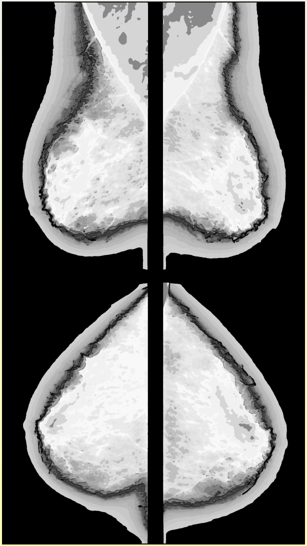
Remark: The most apparent demonstration of contour lines can be seen at the mammogram boundaries characterized by continuously decreasing grey levels. The contour lines may help to evaluate possible contralateral findings or multifocal lesions because regions having similar properties are easily identified visually.

Selection Mask and Segmentation of a Mammogram

selection mask



component segments



Invariance with Respect to Grey-Level Transform

Invariance Property:

log-likelihood image is invariant with respect to arbitrary linear transform of the grey scale of the original image

the transformed data and transformed mixture parameters

$$y_n = ax_n + b, \quad \tilde{\mu}_{mn} = a\mu_{mn} + b, \quad \tilde{\sigma}_{mn} = a\sigma_{mn}, \quad \mathbf{y} = T(\mathbf{x}), \ \mathbf{x} \in \mathcal{S}$$

can be shown to satisfy the EM iteration equations

$$q(m|\mathbf{y}) = q(m|\mathbf{x}), \quad \mathbf{x} \in \mathcal{S}, \quad \tilde{w}_m = w_m, \quad m \in \mathcal{M}$$

$$F(\mathbf{y}|\tilde{\boldsymbol{\mu}}_m, \tilde{\boldsymbol{\sigma}}_m) = \frac{1}{a^N} F(\mathbf{x}|\boldsymbol{\mu}_m, \boldsymbol{\sigma}_m), \quad \tilde{P}(\mathbf{y}) = \frac{1}{a^N} P(\mathbf{x})$$

and therefore the corresponding log-likelihood values differ only by a constat

$$\log \tilde{P}(\mathbf{y}) = -N \log a + \log P(\mathbf{x}), \quad \mathbf{x} \in \mathcal{S}$$

which is removed by fixing the displayed grey-level interval

Concluding Remarks

Local Evaluation of a Log-Likelihood Image:

- log-likelihood image is invariant with respect to arbitrary linear transforms of the grey scale
- need not be trained by other images (non-supervised method)
- it is useful in case of large variability of evaluated textures
- the result of evaluation has a clear statistical interpretation
- can be used to identify abnormal (suspect) locations
- application: fault detection, novelty detection

Log-Likelihood Image of Screening Mammogram:

- **aim:** to facilitate diagnostic evaluation
- **masses:** emphasized as dark regions with contour lines
- **micro-calcifications:** dark spots of the size and form of window
- useful for evaluation of contra-lateral findings and multi-focal lesions

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