Microcalcification Detection in Mammography using Wavelet Transform and Statistical Parameters

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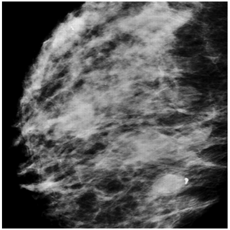
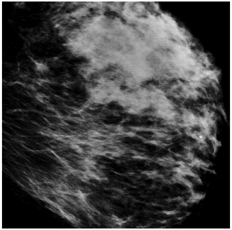
Master's thesis presentation
University of Gothenburg
February 24, 2012

- Introduction
- Wavelet Framework
- One Dimensional Disceret Wavelet Transform
- Two Dimensional Disceret Wavelet Transform
- Microcalcification Detection in Mammography
- Result and Discussion

Introduction

- **Breast cancer** is a cause of cancer death in women. The rates for breast cancer death have been decreasing by earlier detection with specific breast exam called **mammogram** [4].
- A **mammography** is a type of imaging that uses a low-dose x-ray system to examine breasts.
- One of the indicators of breast cancer searched in mammograms are clusters formed by **microcalcifications**.





Introduction

Wavelet based methods

- In [1]: Ted C. Wang, *Detection of microcalcifications in digital mammograms using wavelets*.
  - Decimated algorithms for Daubechies wavelet transform (Db2,Db10).
  - Reconstruct only the wavelet coefficients.
  - High number of false positive results.

- In [2]: K.Prabhu , *Wavelet based microcalcification detection on mammographic images*.
  - Undecimated algorithms for Daubechies wavelet transform (Haar).
  - Microcal detection by the statistics parameters (**skewness, kurtosis**).

- In [3]: M. Gurcan, *Detection of microcalcifications in mammograms using higer order statistics*.
  - Undecimated algorithms.
  - Microcal detection by statistical test based on skewness and kurtosis quantities .

Introduction

- In the **present work**:

  - The **decimated** algorithm for **DWT** with 2 null moments is considered.

  - For each row and column of the sets of wavelet coefficients, **skewness** and **kurtosis** values are computed.

  - The vectors containing these values are then **thresholded**.

  - The crossing of common lines and columns associated to the significant values determine **ROI**.

Wavelet Framework

Definition

Multiresolution Analysis

A *multiresolution analysis* (MRA) is a family of subspaces $V_j \in L^2(\mathbb{R})$ that satisfies the following properties:

I. **Monotonicity**
The sequence is increasing, $V_j \subset V_{j+1}$ for all $j \in \mathbb{Z}$.

II. **Existence of the Scaling Function**
There exists a function $\varphi \in V_0$, such that the set $\{\varphi(. - k) : k \in \mathbb{Z}\}$ is an orthonormal basis for V_0.

III. **Dilation Property**
For each j, $f(x) \in V_0$ if and only if $f(2^j x) \in V_j$.

IV. **Trivial Intersection Property**
$\bigcap_{j \in \mathbb{Z}} V_j = \{0\}$.

V. **Density**
$\overline{\bigcup_{j \in \mathbb{Z}} V_j} = L^2(\mathbb{R})$.

Wavelet Framework

- $\forall$j,k$\in \mathbb{Z}$, the dilation, translation and normalization is given by

$$\varphi_{j,k}(x) = 2^{j/2}\varphi(2^j x - k).$$

- For every $j \in \mathbb{Z}$, W_j is defined to be the orthogonal complement of V_j in V_{j+1}. It means that

$$V_j \perp W_j \quad , \quad V_j \oplus W_j = V_{j+1}.$$

- $\exists$ a function $\psi(x) \in W_0$ such that $\{\psi(2x - k)\}_{k\in\mathbb{Z}}$ is an orthonormal basis for W_0.
  According to the MRA properties , the whole collection $\{\psi_{j,k}; j, k \in \mathbb{Z}\}$, is an orthonormal basis for $L^2(\mathbb{R})$.

Wavelet Framework

- **Scaling and Wavelet equations**
  The scaling function $\varphi(x) \in V_0$ and the wavelet function $\psi(x) \in V_1$ can be written as:

$$\varphi(x) = \sum_{k\in\mathbb{Z}} h_k \varphi_{1,k}(x) = 2^{1/2} \sum_{k\in\mathbb{Z}} h_k \varphi(2x-k),$$

$$\psi(x) = 2^{1/2} \sum_{k\in\mathbb{Z}} g_k \varphi(2x-k).$$

- A function $f_j \in V_j$ can be splitted into its orthonormal components in V_{j-1}, W_{j-1}

$$Pf(x) = \sum_{l=0}^{N_{j-1}-1} c_{j-1,l}\varphi_{j-1,l}(x) + \sum_{l=0}^{N_{j-1}-1} d_{j-1,l}\psi_{j-1,l}(x),$$

  where

$$c_{j-1,l} =< f, \varphi_{j-1,l} >, \quad d_{j-1,l} =< f, \psi_{j-1,l} > .$$

- **Discrete Wavelet Transform**
  Considering $c_{j,l} = f_j(x_l)$ for $l = 0, \cdots, N_j - 1$ and $N_j = 2^{Nmax}$, so

$$c_{j-1,l} = \sum_{k=0}^{D-1} h_{k-2l} c_{j,k}, \quad \text{and} \quad d_{j-1,l} = \sum_{k=0}^{D-1} g_{k-2l} c_{j,k},$$

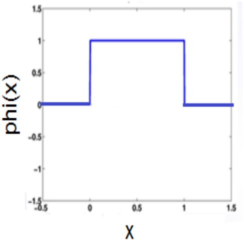
The normalized **Haar** scaling filters are:

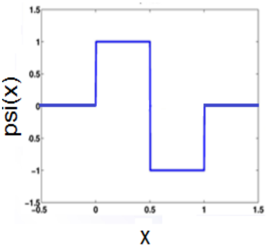
$$h_0 = 1, \quad h_1 = 1.$$

The normalized **Db2** scaling filters are:

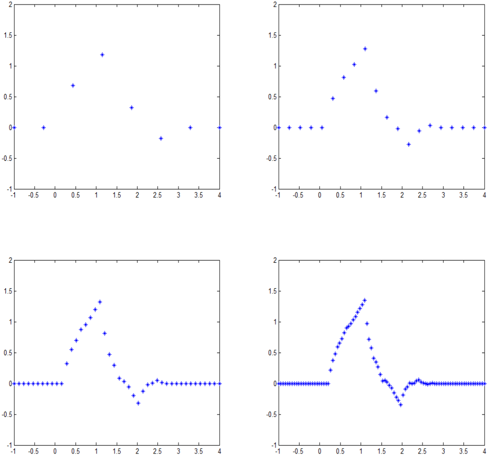
$$h_0 = \frac{1+\sqrt{3}}{4}, \quad h_1 = \frac{3+\sqrt{3}}{4}, \quad h_2 = \frac{3-\sqrt{3}}{4}, \quad h_3 = \frac{1-\sqrt{3}}{4}.$$

Haar Scaling and Wavelet Functions



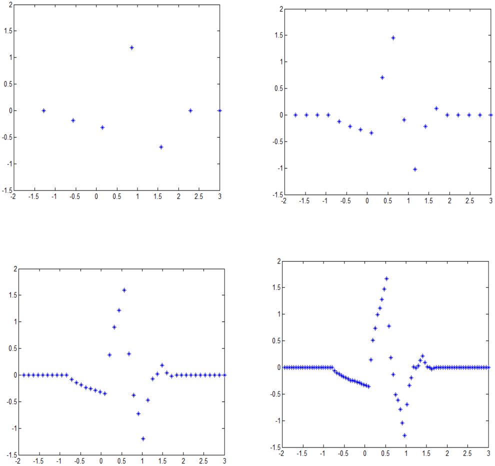


Db2 Scaling Function Construction via Cascade Algorithm Iterations



One Dimensional Discrete Wavelet Transform

Db2 Wavelet Function Construction via Cascade Algorithm Iterations



- **Discrete Inverse Wavelet Transform**
  The coefficients $c_{j,k}$ can be reconstructed by $c_{j-1,l}$ and $d_{j-1,l}$.

$$c_{j,k} = \sum_{l=[\frac{k-D+1}{2}]}^{[\frac{k}{2}]} h_{k-2l} c_{j-1,l}, + \sum_{l=[\frac{k-D+1}{2}]}^{[\frac{k}{2}]} g_{k-2l} d_{j-1,l}.$$

One Dimensional Discrete Wavelet Transform

- **Periodic Extension**

  Perform an even extension by $f_{n+k} = f_k$ for $k > 0$, and $f_{-k} = f_{n-k}$ for $k < 0$ makes the function *periodic*.

- **Zero Padding Extension**

  Add enough zeros to the initial function as $f_k = 0$ for $k < 0$ and $k > n - 1$.

- **Symmetric Extension**

  The function is extended at the end points by reflection.

- **Two Dimensional Scaling and Wavelet Functions**
  To construct the two dimensional wavelet functions from one dimensional scaling function $\varphi(x)$ and wavelet function $\psi(x)$, we define a *scaling function* $\Phi(x, y)$ by:

$$\Phi(x, y) = \varphi(x)\varphi(y),$$

  and three two dimensional *wavelet functions* as

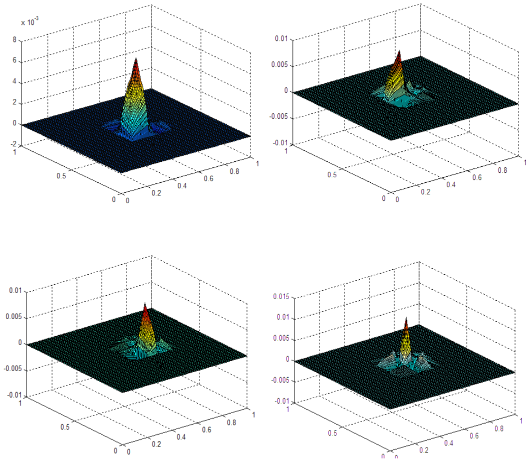
$$\Psi^H(x, y) = \varphi(x)\psi(y),$$
$$\Psi^V(x, y) = \psi(x)\varphi(y),$$
$$\Psi^D(x, y) = \psi(x)\psi(y).$$

- Dilated, translated, and normalized scaling function is defined by

$$\Phi_{j,k}(x, y) = 2^j\Phi(2^j x - k_x, 2^j y - k_y),$$

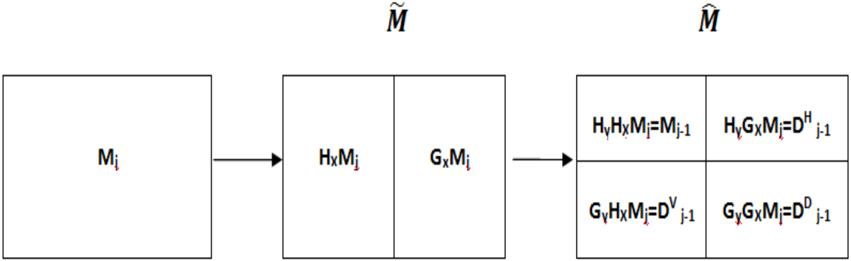
  where $j \in \mathbb{Z}$ and $k \in \mathbb{Z}^2$.

The Scaling and the three corresponding Db2 Wavelet Functions



Two Dimensional Discrete Wavelet Transform

- **Two Dimensional Discrete Wavelet Transform**
  Consider the set of input data represented by the matrix $M = [f_{n,m}]$ where $n, m = 0, \cdots, N_k - 1$ and $N_k = 2^{Nmax}$.



Two Dimensional Discrete Wavelet Transform

- **Example 1. Two Dimensional Db2 Wavelet Transform**
  Consider the input matrix $M = [m_{ij}]$ defined by $m_{ij} = i * x_j$ where $x_j = \frac{j}{16}$ for $i, j = 1, 2, \cdots, 16$.

$$M = \begin{bmatrix}
0.06 & 0.12 & 0.18 & 0.25 & 0.31 & 0.37 & \cdots & 0.68 & 0.7 & 0.81 & 0.87 & 0.93 & 1 \\
0.12 & 0.25 & 0.37 & 0.5 & 0.62 & 0.7 & \cdots & 1.3 & 1.5 & 1.6 & 1.7 & 1.8 & 2 \\
0.18 & 0.37 & 0.56 & 0.7 & 0.93 & 1.1 & \cdots & 2 & 2.2 & 2.4 & 2.6 & 2.8 & 3 \\
0.25 & 0.5 & 0.7 & 1 & 1.2 & 1.5 & \cdots & 2.7 & 3 & 3.2 & 3.5 & 3.7 & 4 \\
0.3 & 0.6 & 0.9 & 1.2 & 1.5 & 1.8 & \cdots & 3.4 & 3.7 & 4 & 4.3 & 4.6 & 5 \\
0.37 & 0.7 & 1.1 & 1.5 & 1.8 & 2.2 & \cdots & 4.1 & 4.5 & 4.8 & 5.2 & 5.6 & 6 \\
0.43 & 0.8 & 1.3 & 1.7 & 2.1 & 2.6 & \cdots & 4.8 & 5.2 & 5.6 & 6.1 & 6.5 & 7 \\
0.5 & 1 & 1.5 & 2 & 2.5 & 3 & \cdots & 5.5 & 6 & 6.5 & 7 & 7.5 & 8 \\
0.56 & 1.1 & 1.6 & 2.2 & 2.8 & 3.3 & \cdots & 6.1 & 6.7 & 7.3 & 7.8 & 8.4 & 9 \\
0.62 & 1.2 & 1.8 & 2.5 & 3.1 & 3.7 & \cdots & 6.8 & 7.5 & 8.1 & 8.7 & 9.3 & 10 \\
0.68 & 1.3 & 2 & 2.7 & 3.4 & 4.1 & \cdots & 7.5 & 8.2 & 8.9 & 9.6 & 10.3 & 11 \\
0.7 & 1.5 & 2.2 & 3 & 3.7 & 4.5 & \cdots & 8.2 & 9 & 9.7 & 10.5 & 11.2 & 12 \\
0.8 & 1.6 & 2.4 & 3.2 & 4 & 4.8 & \cdots & 8.9 & 9.7 & 10.5 & 11.3 & 12.1 & 13 \\
0.87 & 1.7 & 2.6 & 3.5 & 4.3 & 5.2 & \cdots & 9.6 & 10.5 & 11.3 & 12.2 & 13.1 & 14 \\
0.9 & 1.8 & 2.8 & 3.7 & 4.6 & 5.6 & \cdots & 10.3 & 11.2 & 12.1 & 13.1 & 14 & 15 \\
1 & 2 & 3 & 4 & 5 & 6 & \cdots & 11 & 12 & 13 & 14 & 15 & 16
\end{bmatrix}.$$

Two Dimensional Discrete Wavelet Transform

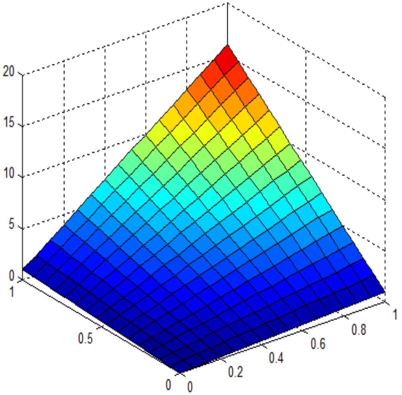


Figure: Function $M = [m_{ij}]_{i,j\in\mathbb{N}}$, defined $m_{ij} = i * x_j$ where $x_j = \frac{j}{16}$ for $i = 1:16$, $j = 1:16$.

Two Dimensional Discrete Wavelet Transform

- **Example 1.1**
  In this example two issues are investigated:
  (1) What happen with coefficients near the boundaries.
  (2) What happen with the wavelet coefficients in each one of the three blocks away from the boundaries.
  $\widehat{M} = 2DWT(M))$.

$$
\widehat{M} = \left[\begin{array}{ccccccc|ccccccc}
0.6 & 1.4 & 2.3 & \cdots & 4.7 & 5.5 & 5.9 & 0 & 0 & 0 & \cdots & 0 & 0 & -1.6 \\
1.4 & 3.3 & 5.1 & \cdots & 10.5 & 12.3 & 13.2 & 0 & 0 & 0 & \cdots & 0 & 0 & -3.6 \\
2.3 & 5.1 & 7.9 & \cdots & 16.3 & 19.2 & 20.5 & 0 & 0 & 0 & \cdots & 0 & 0 & -5.6 \\
3.1 & 6.9 & 10.7 & \cdots & 22.2 & 26 & 27.7 & 0 & 0 & 0 & \cdots & 0 & 0 & -7.6 \\
3.9 & 8.7 & 13.5 & \cdots & 28 & 32.8 & 35 & 0 & 0 & 0 & \cdots & 0 & 0 & -9.6 \\
4.7 & 10.5 & 16.3 & \cdots & 33.8 & 39.6 & 42 & 0 & 0 & 0 & \cdots & 0 & 0 & -1.6 \\
5.5 & 12.3 & 19.2 & \cdots & 39.6 & 46.4 & 49.6 & 0 & 0 & 0 & \cdots & 0 & 0 & -133.6 \\
5.9 & 13.2 & 20.5 & \cdots & 42.3 & 49.6 & 53 & 0 & 0 & 0 & \cdots & 0 & 0 & -14.5 \\
\hline
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\
0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 \\
-1.6 & -3.6 & -5.6 & \cdots & -11.6 & -13.6 & -14.5 & 0 & 0 & 0 & \cdots & 0 & 0 & 4
\end{array}\right]
$$

- **Example 1.2**
  Consider $N = [n_{i,j}]$,

$$n_{i,j} = \begin{cases} m_{i,j} & i,j \neq 8 \\ m_{i,j} + 100 & i,j = 8 \end{cases}$$

By Decompose N ($\widehat{N} = 2DWT(N)$), what happend with the wavelet coefficients on the three blocks? Do they change in a specific position?

$$\widehat{N} = \left[\begin{array}{cccccc|cccccc}
0.6 & 1.4 & 2.3 & 3.1 & \cdots & 5.9 & 0 & 0 & 0 & 0 & \cdots & -1.6 \\
1.4 & 3.3 & 5.1 & 6.9 & \cdots & 13.2 & 0 & 0 & 0 & 0 & \cdots & -3.6 \\
2.3 & 5.1 & \mathbf{11.1} & \mathbf{-10} & \cdots & 20.5 & 0 & 0 & \mathbf{012} & \mathbf{5.5} & \cdots & -5.6 \\
3.1 & 6.9 & \mathbf{-10} & \mathbf{148.9} & \cdots & 27.7 & 0 & 0 & \mathbf{-77.5} & \mathbf{-36} & \cdots & -7.6 \\
3.9 & 8.7 & 13.5 & 18.3 & \cdots & 35 & 0 & 0 & 0 & 0 & \cdots & -9.6 \\
4.7 & 10.5 & 16.3 & 22.2 & \cdots & 42 & 0 & 0 & 0 & 0 & \cdots & -1.6 \\
5.5 & 12.3 & 19.2 & 26 & \cdots & 49.6 & 0 & 0 & 0 & 0 & \cdots & -133.6 \\
5.9 & 13.2 & 20.5 & 27.7 & \cdots & 53 & 0 & 0 & 0 & 0 & \cdots & -14.5 \\
\hline
0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\
0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\
0 & 0 & \mathbf{12} & \mathbf{-77.5} & \cdots & 0 & 0 & 0 & \mathbf{44.7} & \mathbf{20.7} & \cdots & 0 \\
0 & 0 & \mathbf{5.5} & \mathbf{-36} & \cdots & 0 & 0 & 0 & \mathbf{20.7} & \mathbf{9.6} & \cdots & 0 \\
0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\
0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\
0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & \cdots & 0 \\
-1.6 & -3.6 & -5.6 & -7.6 & \cdots & -14.5 & 0 & 0 & 0 & 0 & \cdots & 4
\end{array}\right].$$

Two Dimensional Discrete Wavelet Transform

- **Example 1.3**
  we change just the one value, $d^{D}_{3,5} = 100$, in decomposed matrix $\widehat{N}$ and denote the altered matrix by $\widehat{D}$, then we apply the bi-dimensional inverse wavelet transform ($\mathbf{D} = 2DIWT(\widehat{D})$) to indicate the effect of this change in reconstruction process.

$$\mathbf{D} = \begin{bmatrix}
0.06 & 0.12 & 0.18 & \cdots & 0.5 & 0.56 & 0.62 & 0.68 & 0.7 & 0.81 & 0.87 & 0.93 & 1 \\
0.12 & 0.25 & 0.37 & \cdots & 1 & 1.1 & 1.2 & 1.3 & 1.5 & 1.6 & 1.7 & 1.8 & 2 \\
0.18 & 0.37 & 0.5 & \cdots & 1.5 & 1.6 & 1.8 & 2 & 2.2 & 2.4 & 2.6 & 2.8 & 3 \\
0.25 & 0.5 & 0.7 & \cdots & 2 & 2.2 & 2.5 & 2.7 & 3 & 3.2 & 3.5 & 3.7 & 4 \\
0.3 & 0.6 & 0.9 & \cdots & 2.5 & \mathbf{3.6} & \mathbf{4.5} & \mathbf{-1.9} & \mathbf{6.8} & 4 & 4.3 & 4.6 & 5 \\
0.37 & 0.7 & 1.1 & \cdots & 3 & \mathbf{4.8} & \mathbf{6.2} & \mathbf{-5.2} & \mathbf{9.9} & 4.8 & 5.2 & 5.6 & 6 \\
0.43 & 0.8 & 1.3 & \cdots & 3.5 & \mathbf{-1.4} & \mathbf{-5} & \mathbf{39.8} & \mathbf{-14.9} & 5.6 & 6.1 & 6.5 & 7 \\
0.5 & 1 & 1.5 & \cdots & 4 & \mathbf{7.6} & \mathbf{10.4} & \mathbf{-14.3} & \mathbf{17.6} & 6.5 & 7 & 7.5 & 8 \\
0.56 & 1.1 & 1.6 & \cdots & 4.5 & 5 & 5.6 & 6.1 & 6.7 & 7.3 & 7.8 & 8.4 & 9 \\
0.62 & 1.2 & 1.8 & \cdots & 5 & 5.6 & 6.2 & 6.8 & 7.5 & 8.1 & 8.7 & 9.3 & 10 \\
0.68 & 1.3 & 2 & \cdots & 5.5 & 6.1 & 6.8 & 7.5 & 8.2 & 8.9 & 9.6 & 10.3 & 11 \\
0.7 & 1.5 & 2.2 & \cdots & 6 & 6.7 & 7.5 & 8.2 & 9 & 9.7 & 10.5 & 11.2 & 12 \\
0.8 & 1.6 & 2.4 & \cdots & 6.5 & 7.3 & 8.1 & 8.9 & 9.7 & 10.5 & 11.3 & 12.1 & 13 \\
0.87 & 1.7 & 2.6 & \cdots & 7 & 7.8 & 8.7 & 9.6 & 10.5 & 11.3 & 12.2 & 13.1 & 14 \\
0.9 & 1.8 & 2.8 & \cdots & 8.4 & 9.3 & 10.3 & 11.2 & 12.1 & 13.1 & 14 & 15 & \\
1 & 2 & 3 & \cdots & 8 & 9 & 10 & 11 & 12 & 13 & 14 & 15 & 16
\end{bmatrix}.$$

Thresholding

- **Soft Thresholding** The soft thresholding method on the wavelet coefficients $d^i_{j,k}$ can be performed as:

$$s^i_{j,k} = \begin{cases} d^i_{j,k} - \lambda^i & \text{if} \quad d^i_{j,k} > \lambda^i \\ d^i_{j,k} + \lambda^i & \text{if} \quad d^i_{j,k} < -\lambda^i \\ 0 \quad \textit{otherwise}, \end{cases}$$

- **Hard thresholding** Hard thresholding is another filtering method that is applied on the wavelet coefficients in the following way:

$$s^i_{j,k} = \begin{cases} d^i_{j,k} & \text{if} \quad |d^i_{j,k}| \geq \lambda^i \\ 0 & \text{if} \quad |d^i_{j,k}| < \lambda^i, \end{cases}$$

where $s^i_{j,k}$ are the threshold wavelet coefficients, and $\lambda^i = \mu^i + \alpha\sigma^i$ is the threshold value.

- **Example 2: According to [1]**

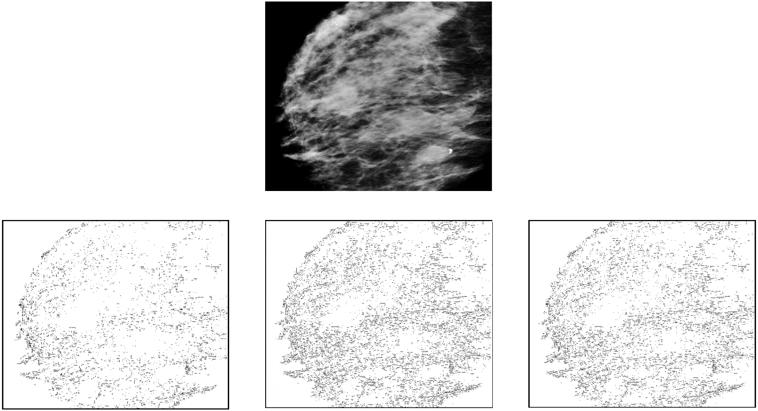


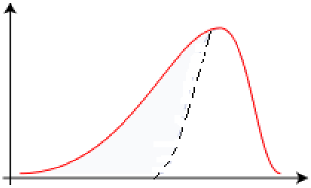
Figure: Edge detection using the soft, modified soft and hard thresholding method.

Statistical Parameters

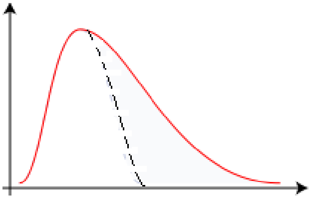
- **Skewness** For a sample of n values, skewness (S) is the third order correlation parameter defined as:

$$S = \frac{\frac{1}{n}\sum_{l=1}^{n}(x_l - \overline{x})^3}{\left(\frac{1}{n}\sum_{l=1}^{n}(x_l - \overline{x})^2\right)^{3/2}},$$

where $\overline{x}$ is the sample mean.



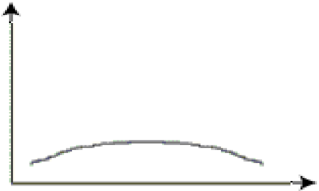
(a) Negative skewness



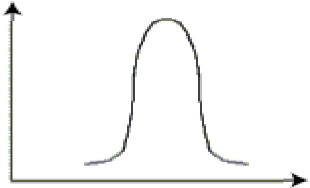
(b) Positive skewness

- **Kurtosis**
  For a sample of n values, kurtosis (K) is the fourth order correlation parameters defined as:

$$K = \frac{\frac{1}{n}\sum_{l=1}^{n}(x_l - \overline{x})^4}{(\frac{1}{n}\sum_{l=1}^{n}(x_l - \overline{x})^2)^2} - 3,$$



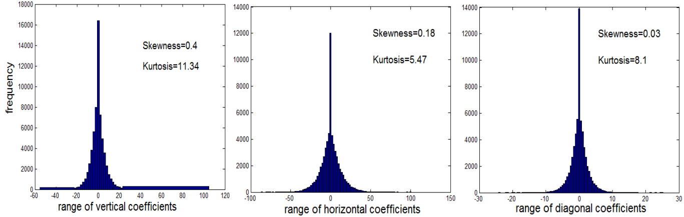
(c) Negative kurtosis



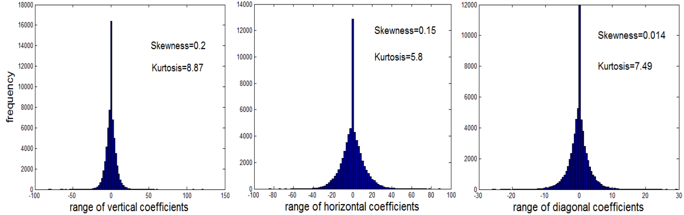
(d) Positive kurtosis

Microcalcification Detection in Mammography

- **W Coeffs Histogram of the Mammography with Microcals**



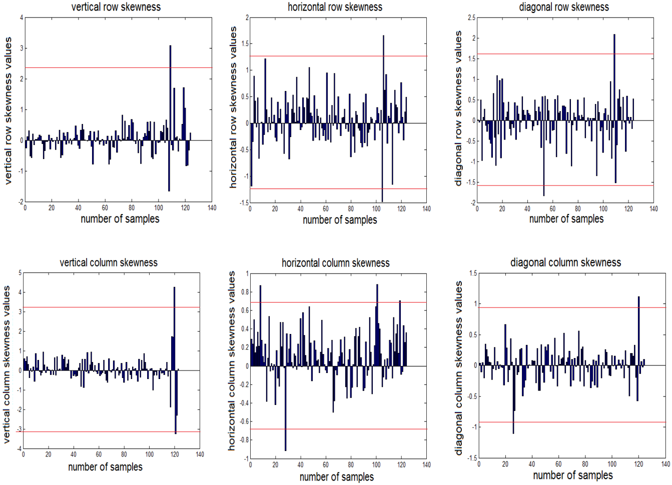
- **W Coeffs Histogram of the Mammography without microcals**



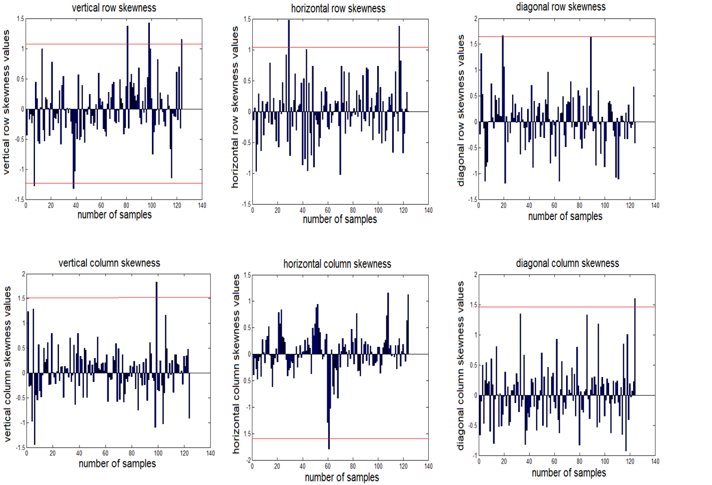
- **Numerical Experiments of Skewness**
- **Example 3, staistical parameters [2,3]**
  - Impute image (I).
  - WT(I)=(C,V,H,D).
  - $S^r(V), S^r(H), S^r(D)$.
  - $S^c(V), S^c(H), S^c(D)$.
  - Threshold of $S^c(.), S^r(.)$.
  - The significant rows and columns are obtained.
  - Intersections of them detect regions.

Microcalcification Detection in Mammography

Subbands Skewness Case with Calcifications



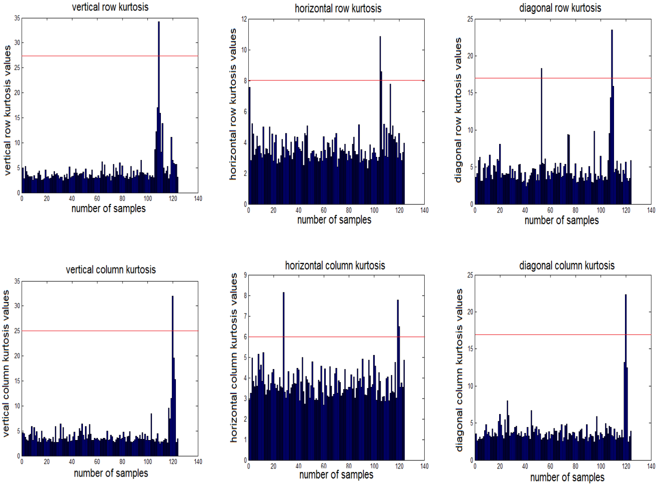
Subbands Skewness Case without Calcifications



- **Numerical Experiments of Kurtosis**
- **Example 4, staistical parameters [2,3]**

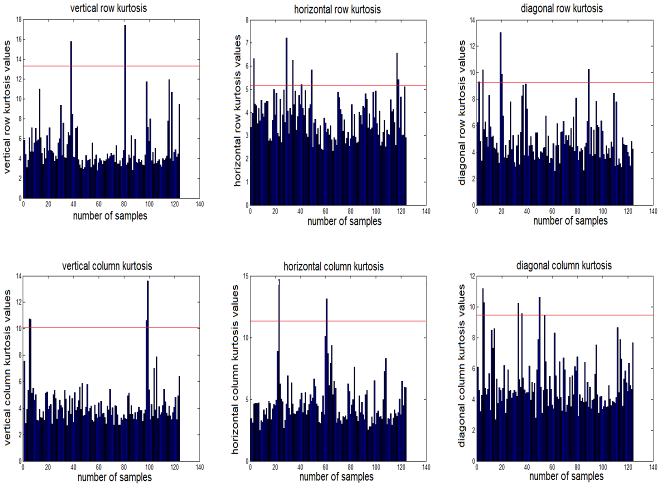
  - Impute image (I).
  - WT(I)=(C,V,H,D).
  - $K^r(V), K^r(H), K^r(D)$.
  - $K^c(V), K^c(H), K^c(D)$.
  - Threshold of $K^c(.), K^r(.)$.
  - The significant rows and columns are obtained.
  - Intersections of them detect regions.

Subbands Kurtosis Case with Calcifications



Microcalcification Detection in Mammography

Subbands Kurtosis Case without Calcifications

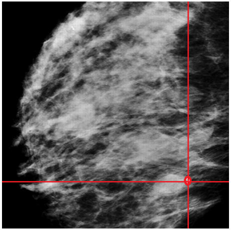


Microcalcification Detection in Mammography

Here the microcalcifications detection method is posed as a hypothesis testing problem in which the null hypothesis, H_0, corresponds to the case of no microcalcifications against the alternative H_1, and it follows the rule Γ based on skewness and kurtosis values,

$$\Gamma(x) = \begin{cases} 0 & S_i < T_i \quad \text{or} \quad K_i < T_i \\ 1 & S_i \geq T_i \quad \text{and} \quad K_i \geq T_i, \end{cases}$$

where T_i is the threshold values determined slightly below the maxima of the row and column skewness and kurtosis values of each subband.



Result and Discussion

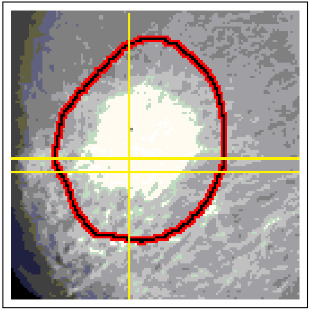
- Now we apply the aforesaid algorithms without performing any wavelet transforms in order to investigate if a previous filtering stage of an image is necessary to detect microcalcifications.

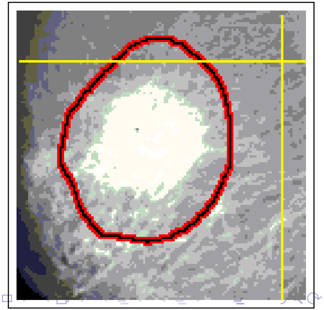
  - Inpute image (I).
  - $S^r(I), S^c(I)$.
  - Threshold $S^r(I), S^c(I)$.
  - $K^r(I), K^c(I)$.
  - Threshold $K^r(I), K^c(I)$.
  - Perform statistical test.
  - The significant rows and columns are obtained.
  - Intersections of them detect regions.

Result and Discussion

- Tow regions of interest selected calculating skewness and kurtosis values of wavelet coefficients.

- A region selected by the analysis of skewness and kurtosis computed directly from the image data.





Result and Discussion

Result of the statistical test based on skewness and kurtosis on 24 digitized mammographies from [7].

Normal mammographies		
Image	Detection	
	skewness	kurtosis
1	0	0
2	0	0
3	0	0
4	0	0
5	0	0
6	0	0

Abnormal Mammograms				
Image	Detection		S, K detections	Identified
	skewness	kurtosis		
7	1	1	same	1
8	4	4	same	4
9	1	1	same	1
10	2	2	same	1
11	2	2	same	2
12	1	1	same	1
13	2	2	same	2
14	2	2	same	1
15	4	4	same	1
16	4	4	same	2
17	4	4	same	2
18	2	2	same	2
19	1	1	same	1
20	6	6	same	6
21	3	3	same	1
22	2	2	same	1
23	2	2	same	1
24	4	4	same	1

References

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(2) K.Prabhu Shetty, V. R. Udupi and K. Saptalakar, *Wavelet Based Microcalcification Detection on Mammographic Images* , Intenational Journal of Computer Science and Network Security, VOL. 9 No. 7, July 2009.
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(4) M. Garcia, A. Jemal, *Global Cancer Facts and Figures 2011*, Atlanta, GA: American Cancer Society (2011).
(5) Ingrid Daubechies, *Ten Lectures on Wavelets* (1992).
(6) http://en.wikipedia.org/wiki/Skewness.
(7) http://marathon.csee.usf.edu/Mammography/Database.html

THANK YOU

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TACK SÅ MYCKET

با تشکر