An Image Analysis of Breast Thermograms

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Abstract: Thermography (infrared imaging) is a non-invasive technique applied for the detection breast cancer. We consider the problem of automatically recognition malignant breast from frontal view thermography image presented as gray scale image. This framework provides insights into several issues: breast *Region of Interest (ROI)* detection, extraction statistical features, extraction features based on texture and co-occurrence matrix.

Key words: Breast thermograms, feature extraction, Gabor wavelets, co-occurrence matrix, texture, Hu moments.

1. Introduction

Mammography is the technique that has the potential to detect very small and very early cancers in the breast. Thermography (also called infrared imaging) is a noninvasive, safe test that can detect breast cancer. Tumors require their own blood supply and thus make a lot of blood vessels in the area of a cancer. The increase in blood supply to feed a breast tumor causes the temperature of the surface of the breast to increase. Breast tumors radiate heat: they are faster-growing and have more vascularity than the surrounding normal tissue. Images are taken by a thermal sensitive camera to capture a digital image based on heat radiating from the body [9]. A computer-assisted interpretation of the digital image helps to determine whether a local abnormality in breast tissue temperature is present, which may indicate the presence of disease.

Each breast's image is placed into one of five thermobiological (*TH*) categories (Figs. 1 and 2):

- (a) *TH1*—Normal uniform non-vascular;
- (b) *TH2*—Normal uniform vascular;
- (c) *TH3*—Equivocal (questionable);
- (d) *TH4*—Abnormal;
- (e) *TH5*—Severely abnormal.

An infrared thermogram is an image of temperature distribution of the breast. Thermograms are viewed as anatomical images in temperature-related colors or grayscale. Each shade of color or gray represents a range of temperatures [5, 8].

In medicine, where the temperature range is more limited a “rainbow” palette is preferred, with red as hot and blue/black as cold (Fig. 3a). In case where a breast infrared thermogram is displayed in gray scale, the brighter pixels have higher temperature values (Fig. 3b). The thermal patterns of two normal, healthy breasts are equally symmetrical uniform temperature distributions [2].

2. Preprocessing and Segmentation

The image is represented as a function of two variables (x,y) . The image in its digital form is usually stored as a two-dimensional array. If $x=\{1,2,\dots,M\}$ and $y=\{1,2,\dots,N\}$ are the spatial domain, then $D=M\times N$ is the set of resolution cells and the digital image F is a function which assigns some greytone value to each and every resolution cell, i.e., $F=M\times N\rightarrow G$.

$$F=\{f(x,y)|(x,y)\in D \text{ and } f(x,y)\in G\} \quad (1)$$

For color image $f(x,y)$ denotes the color value at pixel (x,y) , i.e., $(x,y) = \{f_R(x,y), f_G(x,y), f_B(x,y)\}$.

For black and white images, $f(x,y)$ denotes the gray scale intensity value of pixel (x,y) .

Fig. 1 Thermobiological (TH) categories.

Fig. 2 Risk level of the TH categories.

Fig. 3 Rainbow and grey level palette.

Fig. 4 The block diagram of the proposed method.

Fig. 4 shows the block diagram of the proposed method described in this paper.

An effective approach to automatically detect cancer cases is to study the symmetry between the left and right breast. When the images are relatively symmetrical, small asymmetries may indicate a suspicious region. The thermograms are first automatic segmented.

Segmentation steps are the followings:

(1) Contour detection using Canny algorithm;

(2) Estimation of the breast bottom line based on edge image and breast upper line based on curvature in left and right sides of body;

(3) Segment the left and right breasts rectangular *ROI*'s.

Fig. 5 illustrates the described steps.

The size of left and right breast *ROI* is $X \times Y$. The next stages intend to separate the left and the right breast image.

3. Texture Feature from Gabor Wavelet Transform

Gabor wavelet is a powerful tool to extract texture features and in the spatial domain is a complex exponential modulated by a Gaussian function [3]. In the most general the Gabor wavelet is defined as follows [1, 4]:

$$Gab(x, y, \omega, \theta) = \frac{1}{2\pi\sigma_x\sigma_y} e^{\left[-\frac{1}{2}\left(\frac{x_\theta}{\sigma_x}\right)^2 + \left(\frac{y_\theta}{\sigma_y}\right)^2\right] + j\omega x_\theta} \quad (2)$$

where $j = \sqrt{-1}$, σ_x and σ_y are the scaling parameters of the filter, ω is the radial frequency of the sinusoid, $x_\theta = x\cos\theta + y\sin\theta$, $y_\theta = -x\sin\theta + y\cos\theta$ and $\theta \in [0, \pi]$ specify the orientation of the Gabor filters.

By selecting different center frequencies and orientations, we can obtain a family of Gabor kernels, which can then be used to extract features from an image. Fig. 7 presents the real and imaginary parts of Gabor filters.

Gabor filtered output of the image is obtained by the convolution of the image with Gabor function for each of the orientation/spatial frequency (scale) orientation.

For pixel $F(x, y)$ in an image, its Gabor feature is treated as a convolution:

Fig. 5 Segmentation and ROI extraction. From left to right: Original grey image, Canny edge detection with $th1=43$ and $th2=78$ and left and the right ROI breast image.

Fig. 6 Right and left ROI breast images—top normal images, below malignant images.

Fig. 7 Real (top) and imaginary (below) parts of Gabor filters ($\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$, scale = 4).

$$G_{\omega,\theta}(x,y) = F(x,y) * Gab(\omega,\theta,x,y) \quad (3)$$

For k frequencies and l orientations, we have $k \cdot l$ complex coefficients for each image point.

Features based on the Gabor filters responses can be

$$P_{d,\varphi}(x,y) = \text{card} \left\{ \begin{array}{l} ((x_1, y_1), (x_2, y_2)) \in (XY) \times (XY) \\ \text{for } f(x_1, y_1) = i, f(x_2, y_2) = j \\ (x_2, y_2) = (x_1, y_1) + (d \cos \varphi, d \sin \varphi) \\ \text{for } 0 < i, j < G - 1 \end{array} \right. \quad (8)$$

represented by [6]:

$$\mu(x,y) = \frac{1}{XY} \sum_{x=1}^X \sum_{y=1}^Y G_{\omega,\theta}(x,y) \quad (4)$$

$$\text{std}(x,y) = \sqrt{\sum_{x=1}^X \sum_{y=1}^Y (|G_{\omega,\theta}(x,y)| - \mu(x,y))^2} \quad (5)$$

$$\text{Skew} = \frac{1}{XY} \sum_{x=1}^X \sum_{y=1}^Y \left(\frac{G_{\omega,\theta}(x,y) - \mu(x,y)}{\text{std}(x,y)} \right)^3 \quad (6)$$

$$\text{Kurtosis} = \frac{1}{XY} \sum_{x=1}^X \sum_{y=1}^Y \left(\frac{G_{\omega,\theta}(x,y) - \mu(x,y)}{\text{std}(x,y)} \right)^4 \quad (7)$$

where X, Y is image dimension.

Table 1 presented these parameters for normal and malignant breast left and right ROI's images.

Additional features to describe asymmetry between left and right breast region are based on the co-occurrence matrixes $P_{d,\varphi}(x,y)$ [6].

The co-occurrence matrix $P_{d,\varphi}(x,y)$ counts the co-occurrence of pixels with gray values i and j at a given distance d . The distance d is defined in polar coordinates (d, φ) , with discrete length and orientation. The co-occurrence matrix $P_{d,\varphi}(x,y)$ can now be defined as follows:

Fig. 8 Normal and malignant filtered breast ROI's images. First and third row - left and right breast normal ROI's image; second and fourth row - left and right breast malignant ROI's image.

where $\text{card}\{.\}$ denotes the number of elements in the set.

Let G be the number of gray-values in the image, then the dimension of the co-occurrence matrix $P_{d,\varphi}(x,y)$ will be $G \times G$. So, the computational complexity of the co-occurrence matrix depends quadratically on the number of gray-scales used for quantization.

Features can be extracted from the co-occurrence matrix to reduce feature space dimensionality and the formal definitions of five features from the co-occurrence matrix are done.

The features are:

- (1) Second Angular Moment

$$SAM = \sum_{i=1}^G \sum_{j=1}^G [P_{d,\varphi}(x,y)] \quad (9)$$

- (2) Contrast

$$Con = \sum_{i=1}^G \sum_{j=1}^G (x-y)^2 P_{d,\varphi}(x,y) \quad (10)$$

- (3) Correlation

$$Corr = \frac{\sum_{i=1}^G \sum_{j=1}^G ([xy P_{d,\varphi}(x,y)] - \mu_x \mu_y)^2}{\sigma_x \sigma_y} \quad (11)$$

- (4) Inverse Differential moment

$$IDM = \sum_{i=1}^G \sum_{j=1}^G \frac{P_{d,\varphi}(x,y)}{1+(x-y)^2} \quad (12)$$

- (5) Entropy

$$E = - \sum_{i=1}^G \sum_{j=1}^G P_{d,\varphi}(x,y) \log P_{d,\varphi}(x,y) \quad (13)$$

Table 2 shows these features for the left (*LB*) and right (*RB*) normal and malignant breast *ROI*'s image.

4. Moment-Based Features

The breast *ROI*'s can be represented by the spatial moments of its intensity function. In the spatial case,

Table 1 Texture parameters of the left (LB) and right (RB) breast *ROI*'s image.

Benign breast image						
Parameter	LB <i>ROI</i> breast image			RB <i>ROI</i> breast image		
	<i>std</i>	<i>Skew</i>	<i>Kurtosis</i>	<i>std</i>	<i>Skew</i>	<i>Kurtosis</i>
0°	31.942	1.116	3.001	34.888	0.112	1.618
45°	38.399	0.956	2.009	40.888	-0.089	0.519
90°	33.271	0.995	2.849	32,229	0.570	2.748
135°	42.640	0.647	0.743	40.354	0.101	0.723
Malignant breast image						
Parameter	LB <i>ROI</i> breast image			RB <i>ROI</i> breast image		
	<i>std</i>	<i>Skew</i>	<i>Kurtosis</i>	<i>std</i>	<i>Skew</i>	<i>Kurtosis</i>
0°	27.196	-0.563	4.467	31.302	0.159	1.687
45°	29.761	0.614	2.792	34.048	-0.543	1.044
90°	31.531	-0.919	5.174	30,619	0.250	1.894
135°	31.987	-0.540	2.871	38.194	0.343	0.220

Table 2 Texture parameters of the left (LB) and right (RB) normal and malignant breast *ROI*'s image.

Benign breast image										
Parameter	LB <i>ROI</i> breast image					RB <i>ROI</i> breast image				
	<i>ASM</i>	<i>Con</i>	<i>Corr</i>	<i>IDM</i>	<i>E</i>	<i>ASM</i>	<i>Con</i>	<i>Corr</i>	<i>IDM</i>	<i>E</i>
0°	0.001	173.130	8.662E-4	0.336	7.077	0.001	189.887	7.178E-4	0.292	7.242
45°	7.156E-4	267.995	6.038E-4	0.226	7.572	5.808E-4	359.270	5.180E-4	0.203	7.781
90°	0.001	747.325	5.912E-4	0.291	7.135	0.001	1107.871	4.513E-4	0.300	7.212
135°	5.366E-4	293.376	4.958E-4	0.202	7.851	5.755E-4	301.321	5.407E-4	0.199	7.769
Malignant breast image										
Parameter	LB <i>ROI</i> breast image					RB <i>ROI</i> breast image				
	<i>ASM</i>	<i>Con</i>	<i>Corr</i>	<i>IDM</i>	<i>E</i>	<i>ASM</i>	<i>Con</i>	<i>Corr</i>	<i>IDM</i>	<i>E</i>
0°	0.00	200.520	0.001	0.296	7.039	0.001	223.494	8.506E-4	0.281	7.297
45°	4.821E-4	181.736	9.535E-4	0.127	7.913	4.067E-4	616.283	5.860E-4	0.116	8.099
90°	0.001	654.125	6.230E-4	0.191	7.360	4.257E-4	613.156	6.718E-4	0.112	8.043
135°	4.676E-4	470.031	6.726E-4	0.122	7.998	3.513E-4	357.147	5.827E-4	0.110	8.191

Table 3 Moment invariants for *ROI's* breast images with Fig. 6.

Image	Benign <i>LB ROI's</i> image				Benign <i>RB ROI's</i> image			
	φ 0°	45°	90°	135°	0°	45°	90°	135°
Hu moments								
Hu1	22.5758	21.6936	15.0337	20.3792	16.0810	14.2507	14.1583	16.6080
Hu2	0.6661	2.0352	0.3929	1.4409	1.9940	3.1830	0.6998	6.0098
Hu3	659.3907	867.8238	21.7467	866.7806	116.8156	91.5015	5.6585	173.0833
Hu4	460.0966	645.4099	61.4241	632.2971	45.8474	16.4694	9.2216	31.3254
Hu5	-202361.7656	-384947.75	-2375.6889	-352336.3750	-2583.6867	759.1135	-52.3741	2870.1812
Hu6	-323.2109	-855.6223	-38.2720	-696.7250	-63.2667	8.3043	-7.5937	30.7470
Hu7	369172.6875	747424.8126	4197.7706	9078.3751	412.1985	-663.8193	-13.1033	-2026.007
Image	Benign <i>LB ROI's</i> image				Benign <i>RB ROI's</i> image			
	φ 0°	45°	90°	135°	0°	45°	90°	135°
Hu moments								
Hu1	12.9861	16.9149	11.1434	10.7751	16.3185	11.7599	12.7305	17.6572
Hu2	0.0249	0.2066	0.0086	0.0086	0.1028	0.0582	0.1727	0.5507
Hu3	1.3818	15.3584	0.2102	0.9991	8.6339	1.3814	0.8360	35.0412
Hu4	17.7733	43.1753	2.7171	3.5471	66.2766	59.2879	82.8484	566.5087
Hu5	-33.9289	-41.8188	1.6895	5.6020	-1432.7243	-478.3829	-642.5955	-63704.8906
Hu6	2.7766	13.7490	0.2326	0.3213	-19.5379	-8.0951	-15.1976	-139.0782
Hu7	117.6713	1647.1287	-2.2362	-7.4704	-989.8900	-764.0012	-2182.9470	-49387.6484

$$m_{pq} = \sum_{x=1}^X \sum_{y=1}^Y x^p y^q f(x, y) \quad (14)$$

where $f(x, y)$ is the intensity function representing the image, the integration is over the entire image.

The central moments are given by

$$m_{pq} = \sum_{x=1}^X \sum_{y=1}^Y (x - x_0)^p (y - y_0)^q f(x, y) \quad (15)$$

where (x_0, y_0) are

$$x_0 = \frac{m_{10}}{m_{00}} \text{ and } y_0 = \frac{m_{01}}{m_{00}} \quad (16)$$

Normalized central moment μ_{pq}

$$\eta_{pq} = \frac{m_{pq}}{(m_{00})^\alpha}, \alpha = \frac{p+q}{2} + 1 \quad (17)$$

Using nonlinear combinations of the lower order moments, a set of moment invariants (usually called geometric moments), which has the desirable properties of being invariant under translation, scaling and rotation, is derived. Hu [7] employed seven moment invariants that are invariant under rotation as well as translation and scale change, to recognize characters independently of their position size and orientation.

$$Hu1 = \eta_{20} + \eta_{02}$$

$$Hu2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2$$

$$Hu3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$Hu4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$Hu5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12}) \times [(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) \times [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \quad (18)$$

$$Hu6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$Hu7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12}) [(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03}) [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

The results in terms of the Hu moment invariants for *ROI's* breast images with Fig. 6 are summarized in Table 3.

5. Conclusion

We have presented an approach to analyze breast thermography images. It is clear that Gabor wavelets, statistical texture parameters and invariant texture moments parameters discriminatingly detect benign and malignant breast cancer based on thermography gray scale images. Experimental results show that this approach has high classification accuracy.

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