Evaluation and Selection of Morphological Procedures for Automatic Detection of Micro-calcifications in Mammography Images

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Abstract. In this paper, we present an evaluation of four different algorithms, based on Mathematical Morphology, to detect the occurrence of micro-calcifications in digital mammogram images from the mini-MIAS database. Results provided by TMVA produced the ranking of features that allowed discrimination between real micro-calcifications and normal tissue. ROC area measures the performance of automatic classification, which produced its highest value 0.976 for Gaussian kernel, followed by polynomial kernel, which produced 0.972. An additional parameter, called Signal Efficiency*Purity (SE*P), is proposed as a measure of the number of micro-calcifications with the lowest quantity of noise.

Keywords: Mammography image, mage reconstruction, digital mammography, micro-calcification detection, Mathematical Morphology.

1 Introduction

Breast cancer is the most common malignant neoplasm in western women, being the main cause of death in some countries around the world. Clinical studies revealed that 30% to 50% of breast cancer cases showed micro-calcifications in mammography images and between 60% and 80% were confirmed by histological examination.

Different methods for automatic detection of micro-calcification clusters in digital mammograms have been developed in the past [1, 2]. Recently, research has been focused on simulation 3D of micro-calcification obtained from a micro-CT [3]. However, mammography (which provides information of breast in 2D) is still considered as the most suitable method for detection of micro-calcifications.

The purpose of this work is to analyze the performance of four processing algorithms based on morphological operators reported in the literature for detection of micro-calcifications, and choose the one with the highest sensitivity in order to make an

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automatic classification. Morphological operators were used because the characteristics analyzed by the specialists are based on their morphology, as described in [4,5].

2 Materials and Methods

Data were obtained from the mini-MIAS database [6]. It consisted of mammograms of pixel size 200 microns, dimensions 1024×1024 pixels with 8 bits per pixel (0-black, 255-white). The four algorithms were implemented in MATLAB. First, we remove labels and artifacts on mammograms using reconstruction by dilation [7,8]. The four image processing algorithms evaluated in this work were applied on each entire image. After thresholding, we evaluated the sensitivity and selected the algorithm that retrieved most of micro-calcification. The number of false positives was reduced using a set of features that were inputs of a support vector machine (SVM).

3 Background

Mathematical Morphology was developed by Serra [9]. It is a broad set of operations that process images based on shapes, extracting the relevant information using a structuring element. Two basic operations are erosion and dilation. They produce other operators, known as opening and closing, whose combination give rise to White Top Hat (WTH) and Black Top Hat (BTH) and contrast enhancement κ_{TH} operators [7].

4 Algorithms Analysis

In what follows, four processing algorithms are listed.

4.1 Algorithm 1: Morphological Reconstruction and Extended Maxima Segmentation

This classical algorithm was originally proposed by Soille [7]. The steps were:

1. To apply erosion $\mathcal{E}_B^{(1)}(f)$ to the entire original image f .
2. To apply Opening by Reconstruction: $\gamma_R^{(1)}(f) = R_f^\delta[\mathcal{E}^{(1)}(f)]$, where R_f^δ is the reconstruction by dilation of f , from the eroded image of step 1.
3. To apply White Top-Hat by Reconstruction: $RWTH(f) = f - \gamma_R^{(n)}(f)$.
4. To apply the extended maxima thresholding, for different values of h .

4.2 Algorithm 2: Contrast Operator and Extended Maxima Segmentation

This algorithm was also proposed by Soille [7]. The steps were the following:

1. To apply the Contrast Enhancement Operator κ_{TH} [7] to the original image f .
2. To apply the maxima extended thresholding for different thresholding values of h .
3. To remove objects whose area was greater than 55 pixels. A specialist analyzed the size of micro-calcifications; most of them have less than 50 pixels.

4.3 Algorithm 3: Bicubic Interpolation and Segmentation by Histogram

Part of this algorithm was proposed by Papadopoulos et al. [1]. The steps were:

1. Each entire image f was split in 32 sub-regions.
2. To calculate the mean gray level in the lower 70% region for each sub-region.
3. To apply bicubic interpolation. It produced the image f_{bkg} .
4. To subtract f_{bkg} from the original f . That is $f_{micro} = f - f_{bkg}$.
5. To threshold in two parallel steps:

5.1. *Local thresholding*: (a) to split f_{micro} in 32×32 sub-regions. (b) To select a percentage of pixels with the highest gray level, producing f_1 . (c) To test different percentage values.

5.2. *Global thresholding*: (a) To apply the operator White Top-Hat (WTH) to f . (b) To select pixels with the highest gray level values, producing the image f_2 . (c) To test different percentage values for the thresholding.

6. To apply the intersection f_1 AND f_2 .

4.4 Algorithm 4: Bicubic Interpolation and Extended Maxima Segmentation

The procedure started with the image f_{micro} , obtained in Section 4.3.

1. To threshold f_{micro} in two parallel processes:

1.1. *Local thresholding*: (a) to split f_{micro} in 32×32 sub-regions. (b) To threshold each with the maxima extended transformation, producing a binary image f_1 . (c) To test different values for maxima extended parameter.

1.2. *Global thresholding*: (a) to apply maxima extended transformation, after applying the White Top-Hat Operator (WTH) to the original image f , producing a binary image f_2 . (b) To test different values for maxima extended parameter.

2. To apply intersection of both images: f_1 AND f_2 .
3. To eliminate objects whose area is greater than 55 pixels.

Results of the four algorithms were evaluated using the ground truth information,. The algorithm with the highest sensitivity was selected as the most suitable.

5 Feature Extraction

After enhancement and segmentation for the most suitable processing algorithm, we extracted a set of 65 features in the spatial domain, texture and spectral domains.

6 Spatial Domain Features

They are shown in Table 1 for each object in the binary image. Features f_1 and f_{17} are the same (the area in pixels) so intentionally established for the purpose of proving the effectiveness of ordering in importance, as will be seen in Section 6. Another group of spatial features was computed in blocks of size 17×17 pixels, corresponding to the size of micro-calcifications and normal tissue, as explained in Section 5.3.

Table 1. Spatial features

Feature No.	Name	Feature No.	Name	Feature No.	Name
1	Area	5	Orientation	15	Compactness
2	Eccentricity	6	Solidity	16	Elongation
3	Major axis length	7	Perimeter	17	Area
4	Minor axis length	8-14	Seven Invariant moments of Hu		

For each block centered on the centroid of the object, two new features were obtained: pixel intensity variance $i\text{ var}$ (f62) and energy variance $e\text{ var}$ (f63), defined in [2] as:

$$i\text{ var} = \sum_{m=1}^M \sum_{n=1}^N [f(m,n) - avg]^2$$

$$e\text{ var} = \sum_{m=1}^M \sum_{n=1}^N [f(m,n) - eavg]^2 .$$

The quantity avg is the average of image block and $eavg$ is the energy average [2].

7 Texture Features

Textural properties are based on the Gray Level Co-occurrence matrices [10]. They are built from information of a small block of size 17×17 pixels centered on the centroid of each potential micro-calcification. For each angle between adjacent pixels 0° , 45° , 90° and 135° and a distance $d = 1$, a set of 11 features is obtained, as shown in Tables 2 and 3. The total number of textural features is 44.

8 Spectral Domain Features

Spectral domain features involve the block activity A (feature f64) and the spectral entropy E (feature f65), defined in [14] as:

$$A = \sum_{j=1}^N \sum_{i=1}^M |c(i,j)|$$

$$E = - \sum_{i=1}^M \sum_{j=1}^N a(i,j) \ln(a(i,j))$$

where $a(i,j)$ is related with the coefficients of the discrete cosines transform (DCT) as:

$$a(i,j) = \frac{|c(i,j)|}{A} .$$

Table 2. Texture features for $\theta = 0^\circ$ between adjacent pixels

Feat No.	Name	Feat No.	Name	Feat No.	Name
f18	Contrast	f22	Variance	f26	Difference of variances
f19	Correlation	f23	Sum average	f27	Difference of entropies
f20	Energy	f24	Sum variance	f28	Inverse difference of normalized moments
f21	Entropy	f25	Sum entropy		

Table 3. Remainder of features considered

Feat No.	Name	Feat No.	Name	Feat No.	Name
f29-f39	Idem for $\theta = 45^\circ$	f62	Intensity variance	f65	Spectral entropy
f40-f50	Idem for $\theta = 90^\circ$	f63	Energy variance		
f51-f61	Idem for $\theta = 135^\circ$	f64	Block activity		

9 Results and Discussion

A specialist found 354 micro-calcifications in the mini-MIAS database [6]. Table 4 included parameters of thresholding, sensitivity and the number of false positives for each algorithm. Maxima extended transformation produced higher sensitivity.

Algorithms 1 and 2 used only one control parameter, which resulted in higher sensitivity than 3 and 4. Algorithm 2 retrieved most of the micro-calcifications keeping their morphology. We selected it as the most suitable. Figure 2 shows the results.

Our study quantitatively justified the use of a specific processing algorithm, taking into account the number of true-positives (TP), parameters of each algorithm, the type of breast and the morphology of micro-calcifications.

Table 4. Sensitivity and false positives per algorithm for different parameter values

Algorithm	Parameter type	Parameter value	True Positives	Sensitivity (TP/P)	False positives	Observations
1	extended maxima h	2.5	344	0.9718	1811	(a)
		3	337	0.9520	985	
		4	324	0.9153	578	
2	extended maxima h	6	346	0.9774	2144	(b)
		8	342	0.9661	1218	
		10	335	0.9463	663	
		13	318	0.8993	275	
		15	295	0.8333	151	
3	(c)	5%; 5%	257	0.7260	1041	(d)
		5%; 10%	257	0.7260	1387	
		10%; 5%	272	0.7684	1394	
		10%; 10%	268	0.7571	1909	
4	(e)	2.5; 2.5	335	0.9463	1870	(f)
		2.5; 5	314	0.8870	673	
		5; 5	296	0.8362	325	

- (a) Segmentation did not produce the size neither the shape of the original.
- (b) Distinguish between two closely micro-calcifications.
- (c) Percentage of pixels for Local threshold $pctg_{loc}$; Global threshold $pctg_{glob}$
- (d) Not appropriate for detection in dense-glandular breast.
- (e) Global extended maxima h_{glob} ; Local extended maxima h_{loc} .
- (f) More parameters in segmentation process than in algorithms 1 and 2.

Articles [1, 2] reported in the literature used a specific processing algorithm, but did not mention the number of true-positives retrieved after application.

The stage of automatic classification was done with the Toolkit for Multivariate Analysis (TMVA), which is a software for multivariate classification [11, 12]. Signal and background corresponded to true micro-calcifications and normal tissue.

First, TMVA ranked features that discriminate signal from background. The most significant feature corresponded to the largest separation between signal and background histograms. Table 5 shows the ranking of 65 features. As mentioned in Section 5.1, area was labeled two times (f1 and f17) and TMVA ranked in the first two positions. It means that TMVA effectively ranked features.

For automatic classification data were subdivided into 70% for training and 30% for test. SVM output goes from 0 to 1 as shown in Figure 2(a). Each value corresponded to a specific value of the following quantities [11]: signal efficiency ratio (SE) is the sensitivity; background efficiency ratio (BE) is the specificity; signal purity (SP) is the ratio of objects well detected as signal and the total of objects classified as signal and background; the product of signal efficiency and signal purity (SE*P) is a measure of the highest quantity of signal with the lowest quantity of noise; significance (Sig) is the ratio of the number of instances well detected as signal and the Poisson error associated to detection. TMVA also provided results for the area under ROC curve, as shown in figure 2(b). It plots sensitivity versus specificity.

The statistical significance of a signal in High Energy Physics (HEP) is used as a measure of how good a signal measurement is. A way of maximizing it is to maximize the product Signal Efficiency*Purity. We propose this parameter as another measure of how good the detection system is. Maximizing this value is equivalent to maximize performance.

Fig. 1. (Left) Region diagnosed with micro-calcifications on image mdb253; (center) Image after contrast enhancement operator; (right) Binary image after maxima extended thresholding

Table 5. Ranking of 65 features in spatial domain, texture and spectral domain

Rank	Feat	Rank	Feat	Rank	Feat	Rank	Feat	Rank	Feat	Rank	Feat
1	1	12	23	23	39	34	53	45	49	56	24
2	17	13	56	24	43	35	32	46	35	57	52
3	64	14	63	25	42	36	6	47	57	58	60
4	7	15	45	26	21	37	16	48	59	59	19
5	3	16	34	27	31	38	62	49	30	60	27
6	15	17	55	28	61	39	65	50	38	61	18
7	4	18	33	29	54	40	9	51	51	62	48
8	25	19	44	30	28	41	10	52	26	63	13
9	47	20	22	31	2	42	46	53	11	64	14
10	58	21	8	32	5	43	40	54	29	65	12
11	36	22	50	33	20	44	41	55	37		

It weights the number of micro-calcifications detected with the diagnosis made by the specialist and the detection of all objects made by the classifier. Typical values of SE*P reported in literature of HEP are higher than 0.50 [13]. In the next step, we found the suitable values of kernel parameters in order to obtain the highest value of ROC area, SE and SE*P. They are shown in Table 6.

In Table 6, notice that for linear SVM, the lower the number of features (15 for the linear kernel), the lower both SE*P and the ROC area. Meanwhile, SE is random. However the same number of features for different SVM kernels produced similar results (Gauss $\sigma = 10$ and polynomial). The highest ROC area in this study was 0.976, which corresponded to Gaussian kernel, followed by polynomial kernel, with 0.972. In terms of the parameter SE*P, Gaussian kernel had the highest value (50.07%), as shown in Table 6, which is an acceptable result from the point of view of HEP [13].

Fig. 2. TMVA results for Gaussian kernel with $\sigma = 10$, 50 features and $C = 10$ (left). Areas under ROC curves for lineal, Gaussian and polynomial kernels (right)

Table 6. Results from the automatic classification carried out with SVM

Kernel	Number of features	C	ROC Area	SE (%)	SE*Purity (%)
Gauss $\sigma = 10$	50	10	0.971	82.81	50.07
Gauss $\sigma = 100$	60	100	0.976	81.25	49.33
Linear	15	0.5	0.949	82.81	40.88
Linear	45	0.5	0.959	87.50	41.65
Polynomial $p = 2, \theta = 1$	50	0.1	0.972	82.81	48.23

10 Conclusions

We have presented a quantitative evaluation of four algorithms of processing images based on Mathematical Morphology. The algorithm based on contrast enhancement and thresholding with extended maxima had the highest sensitivity. We proposed the parameter Signal Efficiency*Purity (SE*P) in detection. It provided the higher quantity of micro-calcifications with the lower quantity of background.

Finally, we evaluated performance of SVM for linear, Gaussian and polynomial kernels, testing variations of cost parameter C, kernel parameters and number of features. Gaussian kernel gave the best result for both ROC area and SE*P parameter.

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References

1. Papadopoulos, A., Fotiadis, D.I., Costaridou, L.: Computers in Biology and Medicine 38, 1045–1055 (2008)
2. Zheng, B., Qian, W., Clarke, L.: Digital mammography: mixed feature neural network with spectral entropy decision for detection of microcalcifications. *IEEE Trans. Med. Imaging*. 15(5), 589–597 (1996)
3. Shaheen, E., Van Ongeval, C., Zanca, F., Cockmarin, L., Marshall, N., Jacobs, J.: The simulation of 3D Microcalcification clusters in D digital mammography and breast tomosynthesis. *Medical Physics* 38(12), 6659–6670 (2011)
4. Sickles, E.: *American Journal of Roentgenology* 143, 461–464 (1984)
5. Hong, W.K., Bast, R.C., Hait, W.N., Kufe, E.W., Pollock, R., Weischelbaum, R.R., Holland, J.F., Frei, E.: *Holland-Frei Cancer Medicine*. People's Medical Publishing House, USA (2010)
6. <http://peipa.essex.ac.uk/info/mias.html>
7. Soille, P.: *Morphological Image Analysis. Principles and Applications* Germany. Springer, Germany (2003)
8. Gonzalez, R.C., Woods, R.E.: *Digital Image Processing*. Pearson Prentice Hall, New Jersey (2008)
9. Serra, J.: *Mathematical Morphology*, vol. 1. Academic Press, London (1982)
10. Haralick, R.M., Shanmugam, K., Dinstein, I.: Textural Features for Image Classification. *IEEE Transactions on Systems, Man and Cybernetics* SMC-3(6), 610–621 (1973)
11. Hoecker, A., Speckmayer, P., Stelzer, J., Therhaag, J., Von Toerne, E.: Voss H. TMVA-Toolkit for Multivariate Data Analysis. PoS ACAT 040 (2007)
12. <http://tmva.sourceforge.net/>
13. <http://www.docstoc.com/docs/105178797/Machine-Learning-with-T-MVA>