

A NOVEL SHAPE FEATURE TO CLASSIFY
MICROCALCIFICATIONS

By

Yiming Ma

A Thesis

Submitted to the

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of

Master of Science

Committee:

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_____ Dean of the Graduate School

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By

Yiming Ma

Director: Peter C. Tay, PhD
Assistant Professor
Department of Engineering and Technology

March 2010

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This thesis is dedicated to my parents.

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ABSTRACT

A NOVEL SHAPE FEATURE TO CLASSIFY MICROCALCIFICATIONS

Yiming Ma, M.S.T.

Western Carolina University (March 2010)

Director: Peter C. Tay, PhD

Clinical evident shows that the shape of mammographic calcification is an indicator of the pathology. Microcalcifications (MC) with rough shape are early signs of malignant breast cancer. This thesis proposed a shape metric to help radiologist in classifying regions of interest. Region growing and gradient vector flow algorithm are used to obtain the contour of MC to calculate the normalized distance signature. A three level wavelet decomposition with a Daubechies eight tap wavelet is used to provide a bandpass function and extract the desired shape feature of the MC. A comparison with previously used shape features such as compactness, moment, Fourier descriptors is provided. 58 malignant and 125 benign cases, totaling 368 individual MC, are tested by the proposed method and previously used shape features.

CHAPTER 1: INTRODUCTION

In 2006 cancer was reported as the second leading cause of death in the United States with 559,888 cases, which is equivalent to 23.1% of total deaths [2].¹ In [3], the American Cancer Society (ACS) reported that breast cancer is the most common cancer among women, accounting for nearly 1 in 4 cancers diagnosed in US women.² Table. 1.1 shows ACS's most recent estimates [3] for breast cancer in the United States for 2009³:

Table 1.1: Estimated New Female Breast Cancer Cases and Deaths by Age, US, 2009

Age	In Situ Case	Invasive Cases	Deaths
Younger than 45	6,460	18,640	2,820
45 and older	55,820	173,730	37,350
Younger than 55	24,450	62,520	8,890
55 and older	37,830	129,850	31,280
Younger than 65	40,940	120,540	17,200
65 and older	21,340	71,830	22,970
All Age	62,280	192,370	40,170

It is widely accepted that early detection tests for breast cancer can save many thousands of lives each year [4]. Mammography and palpation are the two conventional ways to screen for breast cancer. Mammography is the process of using X-rays radiation to examine the human breast and is used as a diagnostic as well as a screening tool. The

¹Heart disease is listed as the leading cause with 631,636 cases, which is equivalent to 26.0% of total deaths in [2].

²Men are generally at low risk for developing breast cancer

³Rounded to the nearest 10

presence of clusters of microcalcifications (MC), which are at least three tiny deposits of calcium within a one cm^2 region, could provide information for experienced radiologist to detect the early sign of breast cancer [5]. MC generally have a diameter from 0.1mm to 0.5mm and are hard to detect, especially in dense parenchymal tissue. The presence of MC or MC cluster does not necessarily indicate the presence of malignant cancer. Radiologists evaluate the shape, morphology, and pattern of clusters of MC to determine if a biopsy is warranted.

This paper presents a method to extract a new shape feature from MC found in mammography. The background of computer-aided-analysis and previous work are discussed in Chapter 2; the proposed method is presented in detail in Chapter 3; a comparison of the proposed method with the previous classifier is presented in Chapter 4. Chapter 5 presents a conclusion.

CHAPTER 2: LITERATURE SURVEY

There are variety of proposed methods to classify mammographic region of interests (ROIs). A summary of previous methods used in various stages of computer-aided diagnosis (CAD) are provided. Although the following is not a fully inclusive list, the described features represent a wide range of MC characteristics. Several features such as Haralick features, wavelet features, multi-wavelet features and shape feature [1] are developed as classifier for MC and MC cluster. Individual MC features, statistical texture features, multi-scale texture features as well as fractal dimension features are used in detecting MC [6]. Segmentation process usually takes place together with or after successful detection. The purpose of segmentation is to separate certain featured parts from each other and the background of an image and to divide those into non-overlapping regions. The two main reasons for MC segmentation are to obtain the location of MC to assist radiologists and to classify the abnormalities into benign and malignant categories [7].

In mammography analysis, the background is not uniformly changing due to the non-uniformity of the density of breast tissue. Therefore segmentation of MC usually demands an adaptive method. MC usually appear brighter than its background. If a local threshold method is used to detect MC, then a threshold value for a sub-image and a selection of window size are required. Arikidis et al. present a size-adapted MC segmentation by applying a multiple scale active contour, which is initialized by active ray [8]. Other methods such as non-linear filter, wavelet transform [9] active contour [10] and neural network [11] have also been proposed. Also in [12, 13], the authors proposed another approach to CAD

mammography by detecting a whole MC cluster rather than a single MC.

2.1 Haralick Feature

The Haralick feature analysis [14,15] is known as the spatial gray-level dependence method. This method has previously been used for MC classification in MRI images. The basis for these features is the gray-level co-occurrence matrix \mathbf{H} given by

$$\mathbf{H} = \begin{bmatrix} P(1,1) & P(1,2) & \dots & P(1,N_0) \\ P(2,1) & P(2,2) & \dots & P(2,N_0) \\ \vdots & \vdots & \ddots & \vdots \\ P(N_0,1) & P(N_0,2) & \dots & P(N_0,N_0) \end{bmatrix}. \quad (2.1)$$

where $P(i, j)$ is defined as the number of i^{th} pixel values that are adjacent to the j^{th} pixel

Table 2.1: Table of Haralick features

Angular Second Moment	Contrast
Corelation	Sum of Squares: Variance
Inverse Difference Moment	Sum Average
Sum Variance	Sum Entropy
Entropy	Difference Variance
Difference Entropy	Info. Measure of Correlation 1
Info. Measure of Correlation 2	Max. Correlation Coefficient

value, divided by the total number of such comparisons. The dimension of this matrix is $N_0 \times N_0$, where N_0 is the number of gray levels in the image. Each entry represents the probability that an i^{th} pixel value is adjacent to a j^{th} pixel value. Based on this gray-level co-occurrence matrix \mathbf{H} , Haralick generated 14 texture features listed in Table 2.1.

2.2 Wavelet Feature

Another widely used method is analyzing an image in multi-scale resolution. In [16], a general paradigm for the analysis and application of discrete multiwavelet transforms

is provided. Wavelet analysis is a powerful tool to achieve multi-scale resolution. A computer-aided method to overcome the two main difficulties of detecting MC, which are low contrast between MC and its background and high false positive rate in MC classification, is provided in [17] with applying wavelet to remove the background noise and Markov random field to enhance the recognition of MC.

The extraction of wavelet feature is based on decomposing the image and calculating the entropy and energy of each sub-bands. In a $N \times N$ sub-image, normalized energy and entropy are computed as [1]:

$$\text{normalized energy} = \frac{\sum_i \sum_j x_{ij}}{N^2} \quad (2.2)$$

$$\text{normalized entropy} = - \frac{\sum_i \sum_j \left[\frac{x_{ij}^2}{P^2} \right] \log_2 \left[\frac{x_{ij}^2}{P^2} \right]}{\log_2 N^2} \quad (2.3)$$

where x_{ij} is the $i^{\text{th}}, j^{\text{th}}$ pixel value of the sub-images, and

$$P^2 = \sum_i \sum_j x_{ij}^2. \quad (2.4)$$

2.3 Shape Feature

In [18], the authors proposed a combination of three shape features of individual MC shape and claimed a 100% accuracy of detection by applying a nearest-neighbor method classifier. The mathematical expressions of these three features are:

1. Compactness

$$C = \frac{P^2}{A} \quad (2.5)$$

where P is the length of region perimeter and A is the area of the MC.

2. Moment $F_3 - F_1$

Given $z(i)$, $i = 1, 2, \dots, N$ are the Euclidean distances of the ordered contour pixels to the reference (centroid) point and N is the number of contour pixels, the p^{th} moment is defined as

$$m_p = \frac{1}{N} \sum_{i=1}^N |z(i)|^p . \quad (2.6)$$

The p^{th} central moment is defined as

$$M_p = \frac{1}{N} \sum_{i=1}^N |z(i) - m_1|^p , \quad (2.7)$$

The $F_3 - F_1$ feature is used as the shape feature for classifying MC and is defined as

$$F_3 - F_1 = \frac{M_4^{\frac{1}{4}}}{m_1} - \frac{M_2^{\frac{1}{2}}}{m_1} . \quad (2.8)$$

3. Fourier Descriptor

The Fourier Descriptor is computed by representing each pixel by a complex number $Z_i = x_i + jy_i$, where x_i and y_i are the coordinate of each pixels. The Fourier descriptors are defined as:

$$A(n) = \frac{1}{N} \sum_{i=0}^{N-1} Z_i e^{-j\frac{2\pi}{N}ni} . \quad (2.9)$$

To make the Fourier descriptor invariant to position, size, orientation and starting point of the contour, the Fourier Descriptor is normalized as:

$$NFD(k) = \begin{cases} 0 & k = 0 \\ A(k)/A(1) & k = 1, 2, \dots, N/2 \\ A(k+N)/A(1) & k = -1, -2, \dots, -N/2 + 1 \end{cases} . \quad (2.10)$$

The feature FF (Fourier Feature) is defined based on the NFD as:

$$FF = \frac{\sum_{k=-N/2+1}^{N/2} \|NFD(k)\|/|k|}{\sum_{k=-N/2+1}^{N/2} \|NFD(k)\|} . \quad (2.11)$$

where $\|NFD(k)\|$ denotes the magnitude of $NFD(k)$.

2.4 Other Features

Table 2.2: Table of shape features provided in [1]

1	Number of microcalcifications in cluster
2	Maximum size of microcalcifications in cluster
3	Standard deviation of the size of microcalcifications in cluster
4	Number of microcalcifications with size of one pixel
5	Sum of the area of the microcalcifications in each cluster
6	Maximum value of compactness in cluster
7	Average compactness in cluster
8	Maximum value of F3-F1 in cluster
9	Average value of F3 in cluster
10	Maximum value of F3 in cluster
11	Average F3 in cluster
12	Radius of the circle that best fits the cluster
13	Scattering of the microcalcifications
14	Average gray level of the microcalcifications in cluster
15	Standard deviation of the mean of the microcalcification gray levels in the cluster
16	Maximum standard deviation of the gray levels in each microcalcification
17	Average standard deviation of the gray levels in each calcification in cluster

The features described in this chapter are not a fully complete list. The reader is referred to [1] for a more comprehensive description of the proposed MC feature listed in Table 2.2.

CHAPTER 3: METHODOLOGY

This chapter provides detailed information about the proposed method to classify benign and malignant cases by analyzing the MC shape feature. Firstly, the definition and attribute of the distance signature are introduced. Secondly, explanation of why and how I implemented the algorithm is presented. Finally, the flow chart of the complete method is given in Fig 3.7.

3.1 Region Growing Algorithm

The region growing method (RGM) is adopted to segment MC in my proposed method. The RGM starts from a user specified seed point with a chosen tolerance ($0 \leq \tau \leq 1$, typically $\tau = 0.025$). Initially, the seed point is the only point of a region. A neighboring point value $p(i, j)$ of a region is added to the region if the following criteria is satisfied:

$$(1 - \tau) \frac{(P_{max} + P_{min})}{2} \leq p(i, j) \leq (1 + \tau) \frac{(P_{max} + P_{min})}{2} \quad (3.1)$$

where P_{max} and P_{min} is the maximum and minimum value of the current region and τ is a predefined tolerance. Each iteration grows the region until a maximum number of iterations is performed. The maximum search iteration in my proposed method is set to 500. It has been empirically verified that this depth is sufficient enough for the size of MC being analyzed. An example of the results of region growing with tolerance $\tau = 0.025$ is shown as yellow within a radiologist defined ROI (outlined in red) in Fig. 3.1.

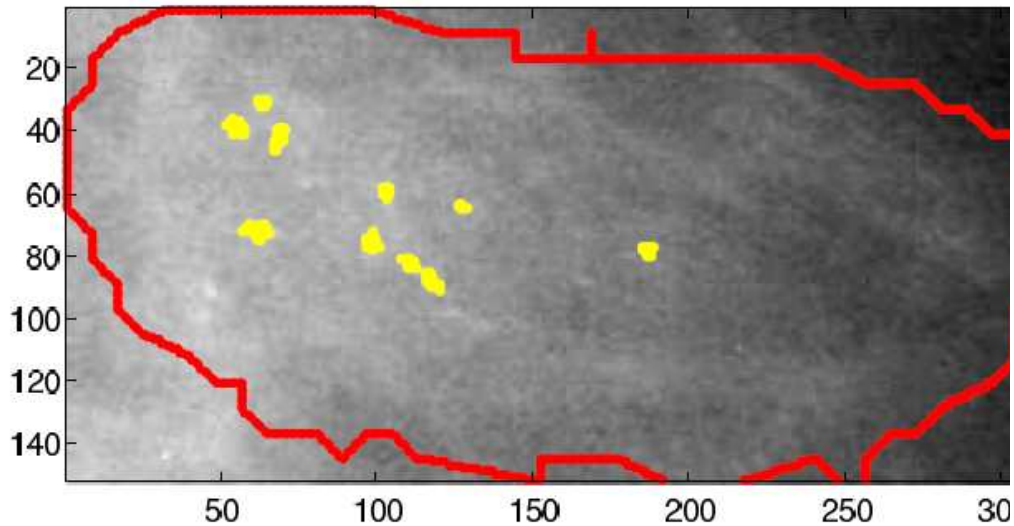


Figure 3.1: An example of the RGM. The yellow pixels are the result of the region growing segmentation.

3.2 Gradient Vector Flow Active Contour

The gradient vector flow (GVF) active contour, or snake [19] is used to get an order set of close contour points from the region growing results. Active contours are widely used in computer vision and image processing applications. Particularly it is used to outline boundaries of an object or other desired features within an image [20]. The snakes are curves defined within an image domain, which could move according to the internal force and the external gradient field until finally reaching a balanced state. Since the external gradient field is computed from the image data, the snake will conform to the boundaries of the object or other desired image feature. An example of active contour is provided in Fig. 3.2 [19]. The dynamic snake equation is defined in equation (3.2):

$$\mathbf{X}(s,t) = \alpha \mathbf{X}''(s,t) - \beta \mathbf{X}'(s,t) + V(x,y) \quad (3.2)$$

where $\mathbf{X}(s,t) = [x(s,t), y(s,t)]$ is the snake and $s \in [0, 1]$, \mathbf{X}' and \mathbf{X}'' denote the first and second derivatives of \mathbf{X} with respect to s , α and β are weighting parameters applied to

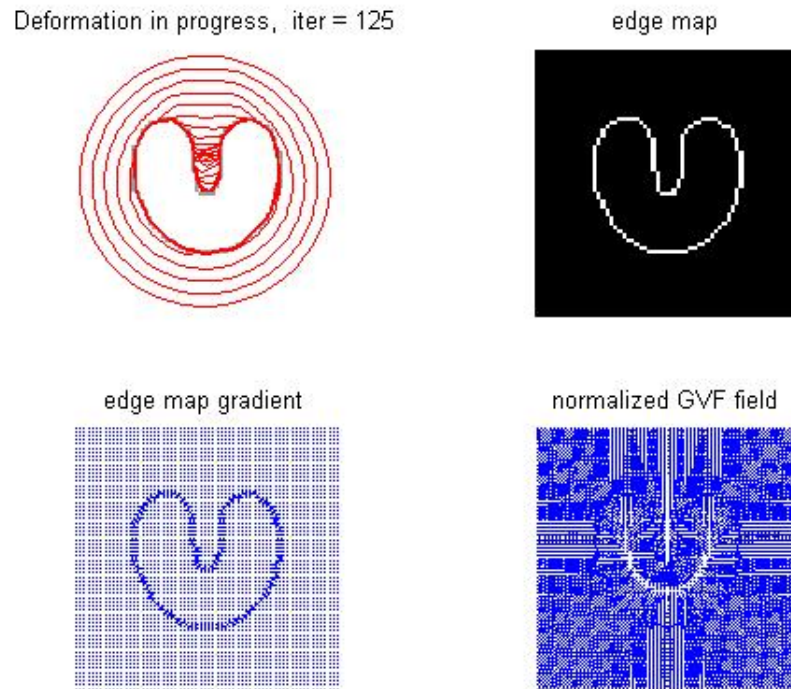


Figure 3.2: An example of active contour

the snakes tension and rigidity, respectively. The last term of equation (3.2) is $V(x,y) = [u(x,y), v(x,y)]$, the gradient vector field that minimized the energy functional ε , defined in equation (3.3)

$$\varepsilon = \int \int \mu(u_x^2 + u_y^2 + v_x^2 + v_y^2) + |\nabla f|^2 |V(x,y) - \nabla f|^2 dx dy \quad (3.3)$$

where $f(x,y)$ is the edge map and μ is a parameter governing the tradeoff between the first term and the second term in the integrand.

3.3 A Normalized Distance Signature

The signature of a shape is used extensively in image processing shape analysis applications. The shape signature can be generated in various ways [21]. In [18], an order set

of close contour points of each MC within a radiologist defined ROI is required to extract shape features. A normalized distance signature is extracted from the order set of close contour from GVF contour described in the previous section of this chapter. The distance signature is defined as the Euclidean distance of the ordered contour point to the centroid [18] in equation (3.4)

$$\text{dist}[i] = \sqrt{(x_i - x_c)^2 + (y_i - y_c)^2}. \quad (3.4)$$

It should be noted that this distance signature is invariant to various affine transformations like translations and rotations. The distance signature of equation (3.4) will change with the size of an object. The scale variance is partly due to the digitizing error of the coordinate of the contour point, which in most of the cases has a negligible effect. Another reason why this signature is only pseudo-scale invariance is that a length of the normalized signature in equation (3.5) varies with respect to the size of the object and sampling of the contour. To make it pseudo-invariant to scale, the distance signature is normalized by dividing the mean. The normalized distance signature used in the proposed feature is

$$\widetilde{\text{dist}}[i] = \frac{\text{dist}[i]}{\text{mean}(\mathbf{dist})}. \quad (3.5)$$

This normalization provides a pseudo-scale invariance to the distance signature.

3.4 A Novel Roughness Metric

The novel aspect of the proposed method is using frequency analysis of the normalized distance signature to evaluate the roughness of a MC contour. Bandpass filtering is provided by a three level wavelet decomposition and reconstruction with a Daubechies eight tap wavelet. The reconstruction using only the third detail wavelet coefficients \mathbf{D}_3 is used to compute the roughness feature. In Fig. 3.3, the filtering processes is illustrated by a

block diagram. The filters $F_a(z)$, $G_a(z)$, $F_s(z)$, and $G_s(z)$ denote the z -transforms of the eight tap Daubechies analysis scaling function, analysis wavelet, synthesis scaling function, and synthesis wavelet, respectively. The processes denoted by $\downarrow 2$ and $\uparrow 2$ indicate down sampling and up sampling by a factor of two, respectively.

An example using a circle, an ellipse and a star shaped contour is displayed in Fig. 3.4.

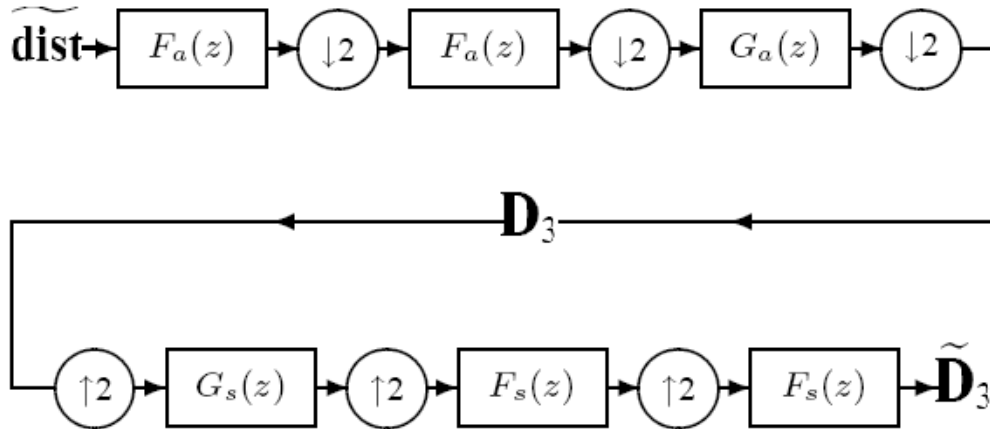


Figure 3.3: Wavelet decomposition of the normalized distance signature $\widetilde{\text{dist}}$ and reconstruction from only the \mathbf{D}_3 coefficients.

The normalized distance signatures of circle, ellipse and star are shown in Fig. 3.5 as the green, blue, and red plots, respectively. The performance of the proposed metric is demonstrated by analyzing these three shapes. The filtering result of the normalized distance signatures is shown in Fig. 3.6.

Low frequency oscillations of the normalized distance signature indicate smoothness of the analyzed contour. It is shown by Fig. 3.5 that the normalized signature of the circle is constant and the star shaped contour has significantly higher frequency. To extract this higher frequency component of each normalized distance signature, reconstruction with only the $\widetilde{\mathbf{D}}_3$ coefficient of the normalized distance signature is employed. Fig. 3.6 shows the $\widetilde{\mathbf{D}}_3$ coefficient reconstruction of the circle, ellipse and star as the green, blue,

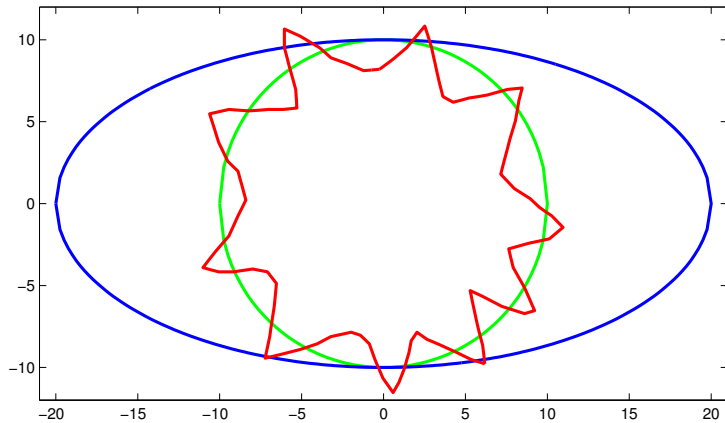


Figure 3.4: Example of an ellipse, a circle, and a star contours.

and red plots, respectively. A larger maximum absolute value of the $\tilde{\mathbf{D}}_3$ reconstruction in Fig. 3.6 indicates a rougher contour. Therefore, the proposed novel metric α to classify MC is the maximum absolute value of reconstruction from the \mathbf{D}_3 coefficients

$$\alpha = \max(|\tilde{\mathbf{D}}_3|). \quad (3.6)$$

The reason why absolute value is used as the shape feature is that a value in the reconstruction of $\tilde{\mathbf{D}}_3$ would indicate a local difference. Whether this local difference will cause a positive or negative peak in the reconstruction of $\tilde{\mathbf{D}}_3$ is dependent on how the filters are implemented. Also, a larger amplitude of the peak in the reconstruction of $\tilde{\mathbf{D}}_3$ is attained by larger local differences. Further the absolute value makes the metric invariant to reflecting the contour about some line. A list of the roughness value α defined in equation (3.6) for the circle, ellipse, and the star shaped contour, as well as analysis using previously proposed shape feature is provided in Table 3.1. From Table 3.1, the roughness metric α has a desired relation that is substantially larger for the rough star shaped (0.1528) contour than for the circle (0) and the ellipse (0.0095).

A flow chart of my shape analysis method is shown in Fig. 3.7.

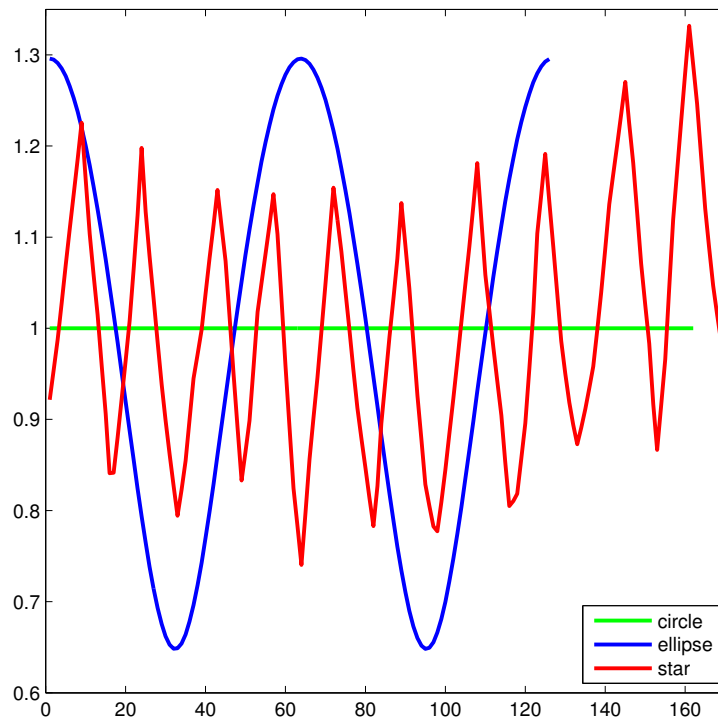


Figure 3.5: The normalized distance signatures ($\widetilde{\text{dist}}$).

Table 3.1: Previously published and proposed α features of the contours shown in Fig. 3.4

Contour	Moments	Fourier descriptor	Compactness	α
circle	0	0.1166	12.5571	0
ellipse	0.0377	0.1215	14.9301	0.0095
star	0.0297	0.0587	29.136	0.1528

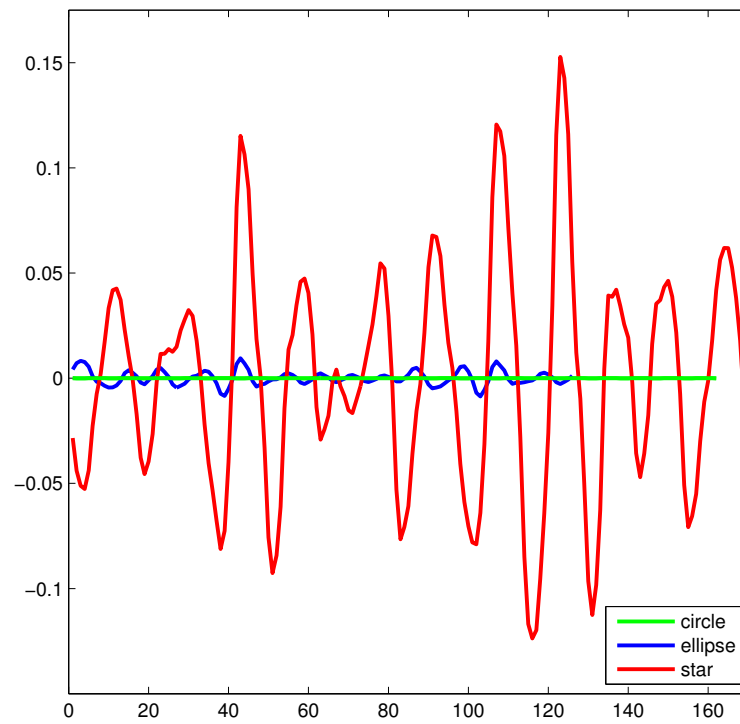


Figure 3.6: Approximations of the normalized distance signatures in Fig. 3.5 from using only the \mathbf{D}_3 wavelet coefficients.

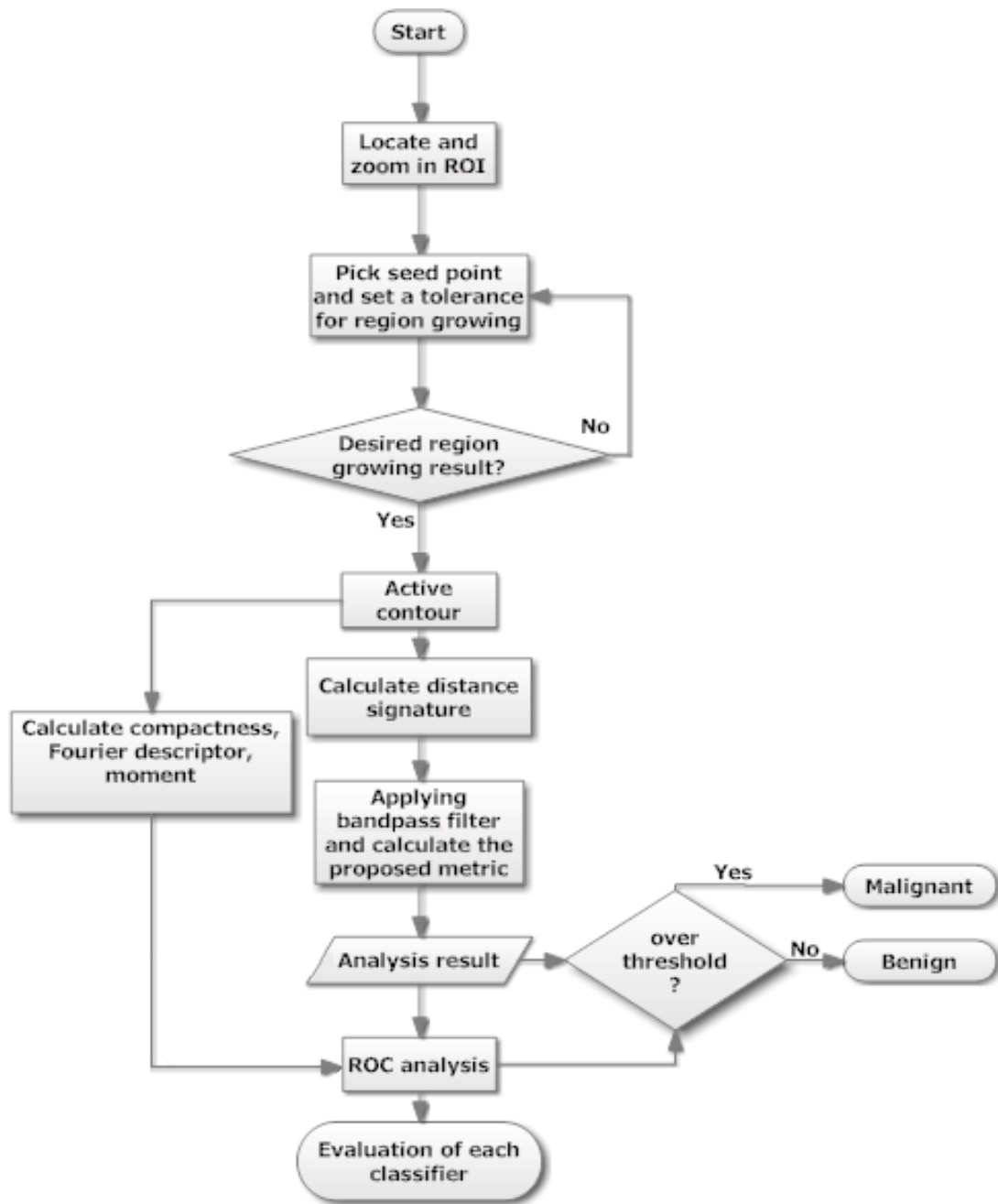


Figure 3.7: Flowchart of the proposed method

CHAPTER 4: EXPERIMENTATION AND RESULT

An experiment was performed to evaluate the robustness of my proposed roughness metric. The experiment tested my proposed metric against three previously published shape metrics.

4.1 The Experimentation

A data mining of DDSM shows that mammograms with certain characteristics are problematic to diagnosis. The number of each lesion type in DDSM and the ratios of benign cases in each lesion type are listed in Table 4.1 and Table 4.2, respectively. In Table 4.2,

Table 4.1: Numbers of each lesion types in DDSM

Type\Distribution	Cluster	Linear	Segmental	Regional	Diffuse
Punctate	82	4	20	6	4
Amorphous	135	6	33	11	4
Pleomorphic	716	70	140	27	0
Round & regular	8	0	0	0	0
Luscent center	0	1	0	0	0
Fine 2 branching	28	36	19	2	0

the ratio of benign to total number of pleomorphic and cluster MC cases is close to 0.5. This indicates that it is difficult to classify mammograms with this type of lesion. An example of a DDSM case of pleomorphic and clustered mammogram with associate data file is included in Appendix A. Other cases that also have ratio of benign cases close to 0.5

Table 4.2: Ratios of benign cases

Type\Distribution	Cluster	Linear	Segmental	Regional	Diffuse
Punctate	0.65	1.0	0.8	0.6	1.0
Amorphous	0.79	0.3	0.79	0.45	0.5
Pleomorphic	0.59	0.17	0.3	0.2	N/A
Round & regular	0.75	N/A	N/A	N/A	N/A
Luscent center	N/A	1.0	N/A	N/A	N/A
Fine 2 branching	0.18	0.25	0	1.0	N/A

are ignored due to the small number of total cases.

The experiment was performed using 183 DDSM pleomorphic and clustered MC cases, from DDSM. This set included 58 malignant and 125 benign cases. There were a total of 368 individual MC that were analyzed. All 183 cases had only one radiologist defined ROI associated with each mammogram. The sole ROI contained BIRADS® pleomorphic and clustered MC and biopsy was recommended in all cases. Only MC from the ROI were analyzed. The robustness of the segmentation of each MC was supervised by setting the tolerance parameter by trial and error so that a robust segmentation was attained. The GVF algorithms was also supervised to ensure that the contour of each MC was correctly captured. The initial curve of GVF was a small circle centered at the centroid of the MC determined by the region growing algorithm. In [5], a radiologist prescribe that a cluster can be classified as benign when all MC within the ROI are round or oval. Thus, a single rough shaped MC could indicate the development of malignant cancer. Therefore the maximum α attained by a selected MC in a ROI is used to classify the ROI as benign or malignant. The shape features of compactness, moment and Fourier descriptor, as described in [18] are used as a comparison to test improvements provided by my shape feature.

4.2 Receiver Operating Characteristic

The receiver operating characteristic (ROC) graph is a technique to visualize the sensitivity and specificity of the performance of a certain classifier. It has been used in signal detection theory to describe the relation of hit rate and false alarm rate [22]. ROC is widely used to evaluate medical decision algorithms. The true positive rate (TPR), also called hit rate, represent the probability that a system could correctly classify given it is actually positive. The false positive rate (FPR), also called false alarm rate, indicates how often the system classify an actual negative as a positive. True positive rate (TPR) and false positive rate

		actual value		total
		p	n	
prediction outcome	p'	True Positive	False Positive	P'
	n'	False Negative	True Negative	N'
total		P	N	

Figure 4.1: Relations between TPR, FPR, FNR and TNR

(FPR) are defined in equation (4.1) and equation (4.2) respectively, where TP is number of true positives, FN is number of false negatives, FP is number of false positives and TN is true negatives. The TPR and FPR are mathematically defined as

$$TPR = \frac{TP}{TP + FN} \quad (4.1)$$

$$FPR = \frac{FP}{FP + TN}. \quad (4.2)$$

To show the significance of the ROC, let's assume benign MC have a shape feature, whose values have a Gaussian distribution with $\mu = 1$ and $\sigma^2 = 0.49$, while the same feature of malignant MC have a Gaussian distribution with $\mu = -1$ and $\sigma^2 = 0.49$ as shown in the left plot of Fig. 4.2. If we choose 0.5 as the threshold of this classifier to determine the pathology, the TPR would be represented by the shaded part in the center plot of Fig. 4.2 while the FPR is represented by the shaded part in the right plot of Fig. 4.2. Though we

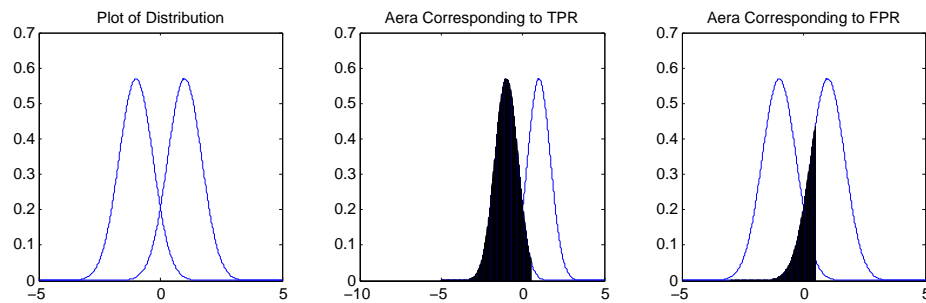


Figure 4.2: An example of distributions to illustrate TPR and FPR. These distribution are not actual.

could choose a different threshold to achieve a desired TPR or FPR, performance of the classifier is dependent on the overlap of the distributions. The ROC graph displays the dependence of the threshold on FPR and TPR. FPR is indicated on the x-axis and TPR is indicated on the y-axis. Fig. 4.3 shows an example of a ROC curve. It is widely quantified that a classifier with higher AUC (area under curve) is considered a better one, because it could achieve a higher TPR than one with lower AUC at the same FNR. The ROC curve and AUC are used to judge the performance of a classifier. It's ideal to get a 100% TPR with a 0% FPR. But in reality there is a trade off between these two. A simulated ROC curve is plotted in Fig. 4.3, if the threshold corresponding to the circle point on the ROC in Fig. 4.3 is used, we could achieve 35% FNR and 55% TPR performance.

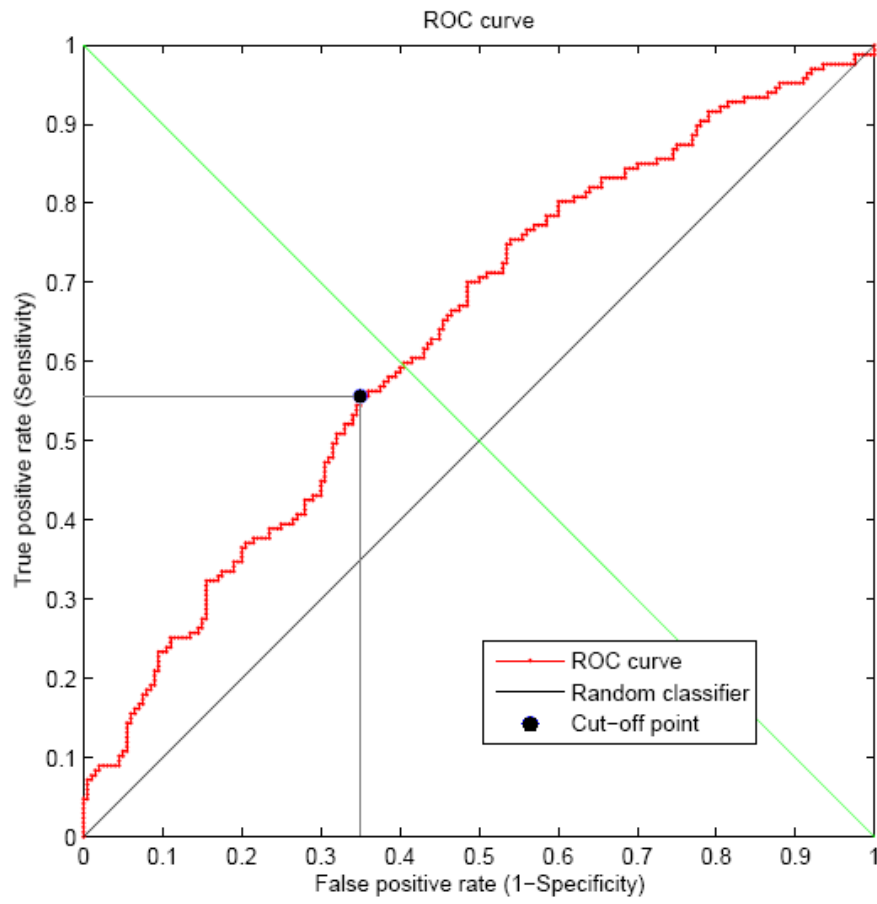


Figure 4.3: A simulated ROC curve

Table 4.3: AUC in Fig. 4.4

Feature	AUC %
Proposed α	96.4
Moment	78.0
Fourier descriptor	73.9
Compactness	56.5

4.3 Test Result

The shape feature of each of the 368 MCs was computed using my proposed method to produce an α value, along with the Fourier descriptor, moment and the compactness shape feature. These computed shape feature measures are listed in Table C.1. Only the maximum α from each ROI was used to classify the pathology. Appendix B lists the computed shape feature measures for the MC which has the maximum value in each ROI. The F, FF and C data in Appendix B were used to generate the ROC and calculate the AUC for those features. The ROC of the proposed a measure, along with the ROCs of the moment, Fourier, and compactness measures are shown in Fig. 4.4. The corresponding AUC of each these four ROCs are listed Table 4.3. The ROC of my proposed shape measure shows better diagnostic accuracy than the compactness, moment and Fourier descriptor measures. The ROI of the α measure has a higher TPR at a cost of lower FPR as shown in Fig. 4.4. The AUC of my proposed metric is significantly higher than the other three.

Since missing a suspicious malignant case could be fatal, achieving a 100% TPR is the priority in setting the threshold for the classifier. With the threshold for the proposed method set at $\alpha = 0.2522$, all the malignant ROIs are correctly identified with a 20% FPR. Thus, it would have save 80% of the suspicious but benign cases from biopsy. Therefore 80% (100 out of 125) of the tested cases were correctly identified as benign, and all 58 tested malignant cases were correctly identified.

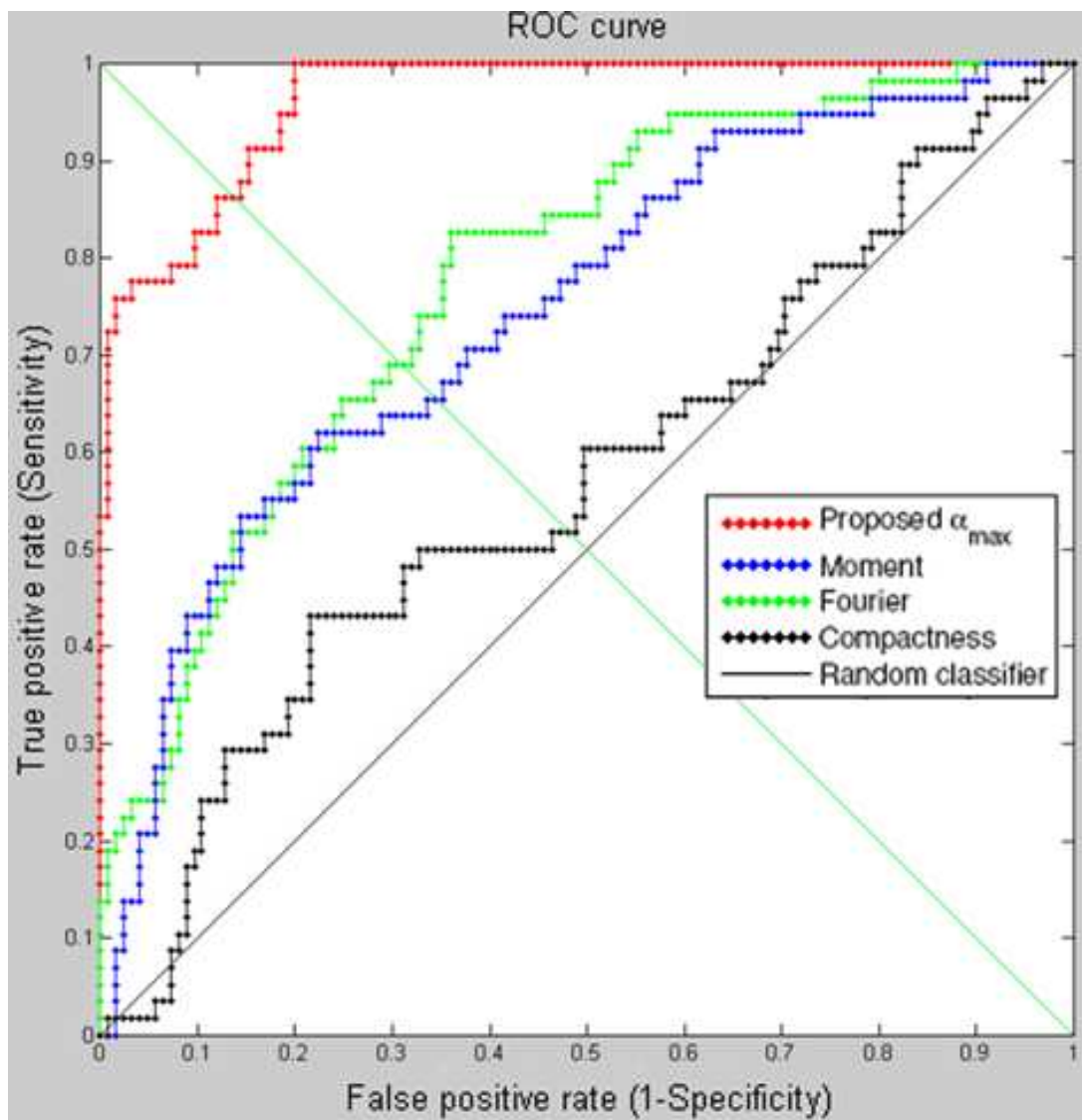


Figure 4.4: ROC of the proposed method, compactness, moment, Fourier descriptor

CHAPTER 5: CONCLUSION

A computer aided method to assist radiologists in classifying mammograms with pleomorphic and clustered MC as well as other hard to diagnosis cases is presented in this thesis. As discussed in Chapter 1, it is standard to use mammography to detect early signs of breast cancer. Data mining of DDSM shows that ROIs with pleomorphic and clustered MC is problematic for radiologist to diagnose. Clinical evidence shows that ROIs containing tiny MC that are all round and oval have less of a chance in developing into malignant cancer [5]. Based on Sickles' claim in [5], an irregularly rough shaped MC could be an early sign of potentially malignant cancer.

The proposed method starts with a region growing process to segment the selected MC, followed by the generation of a GVF active contour to define the outer contour of ordered points of each segmented MC. Then a distance signature sequence is generated from the Euclidean distance of each contour points to the centroid. After normalizing the distance signature, a novel feature α to represent roughness of the shape is extracted by bandpass filtering and full resolution reconstruction of the normalized distance signature. A shape feature α is computed from the filtered sequence is produced by the maximum absolute value of the bandpass approximation of the normalized distance signature using only the \mathbf{D}_3 wavelet coefficients. High α values indicate rough shaped contours. An evaluation using ROC and AUC was performed. It was shown that the maximum α attain by a MC of each ROI was a better classifier of malignant or benign than the individual Fourier descriptor, moment and compactness features. Finally a threshold value for α is set by

ROC analysis to achieve 100% TPR at a low cost of 20% FPR. Therefore, the experimentation in this thesis provides evidence that my proposed shape analysis and metric is better classifier than any of the three previously published shape metrics.

Appendices

APPENDIX A: AN EXAMPLE OF THE DDSM DATA

Table A.1: An example of the DDSM data

Pathology	Benign
Case No.	1265
Machine	HOWTEK
filename	A_1265_1.RIGHT_MLO
overlay file	A_1265_1.RIGHT_MLO.OVERLAY

A.1 Content of the associated ics file

ics_version 1.0

filename A-1265-1

DATE_OF_STUDY 25 1 1995

PATIENT_AGE 48

FILM

FILM_TYPE REGULAR

DENSITY 3

DATE_DIGITIZED 23 7 1998

DIGITIZER HOWTEK 43.5

SEQUENCE

LEFT_CC LINES 6556 PIXELS_PER_LINE 4111 BITS_PER_PIXEL 12 RESOLUTION

43.5 NON_OVERLAY

2 2 4 4 4 4 2 2 2 2 2 3 3 3 3 3 2 2 2 2 2 4 4 4 4 4 2 2 2 2 2 2 2 2 2 4 4 4 4 4 2 2 2 2 2 2 2
 2 2 3 3 3 3 3 2 2 2 2 2 4 4 4 4 4 2 2 2 2 2 2 2 2 2 2 4 4 4 4 3 3 3 3 4 2 2 2 2 2 4 4 4 4 4 2 2
 2 2 2 4 4 4 4 4 4 4 4 4 2 2 2 2 2 4 5 5 5 5 4 4 4 4 4 4
 4 4 4 4 6 6 6 6 6 4 4 4 4 4 4 4 4 4 6 6 6 6 6 4 4 4 4 4 6 6 6 6 5 5 5 5 5 6 6 6 6 6 4 4 4 4 4 6
 6 6 6 6 4 4 4 4 4 6 6 6 6 6 4 4 4 4 6 6 6 6 6 4 4 4 4 4 6 6 6 6 6 6 6 6 4 4 4 4 4 6 6 6 6 6 6
 6 6 6 6 5 5 5 5 5 #

A.3 The image data

MC_BEN_1265 right medio-lateral raw pixel is displayed as a gray scale image in Fig. A.1.

The circle in Fig A.1 is the ROI assigned by a radiologist.

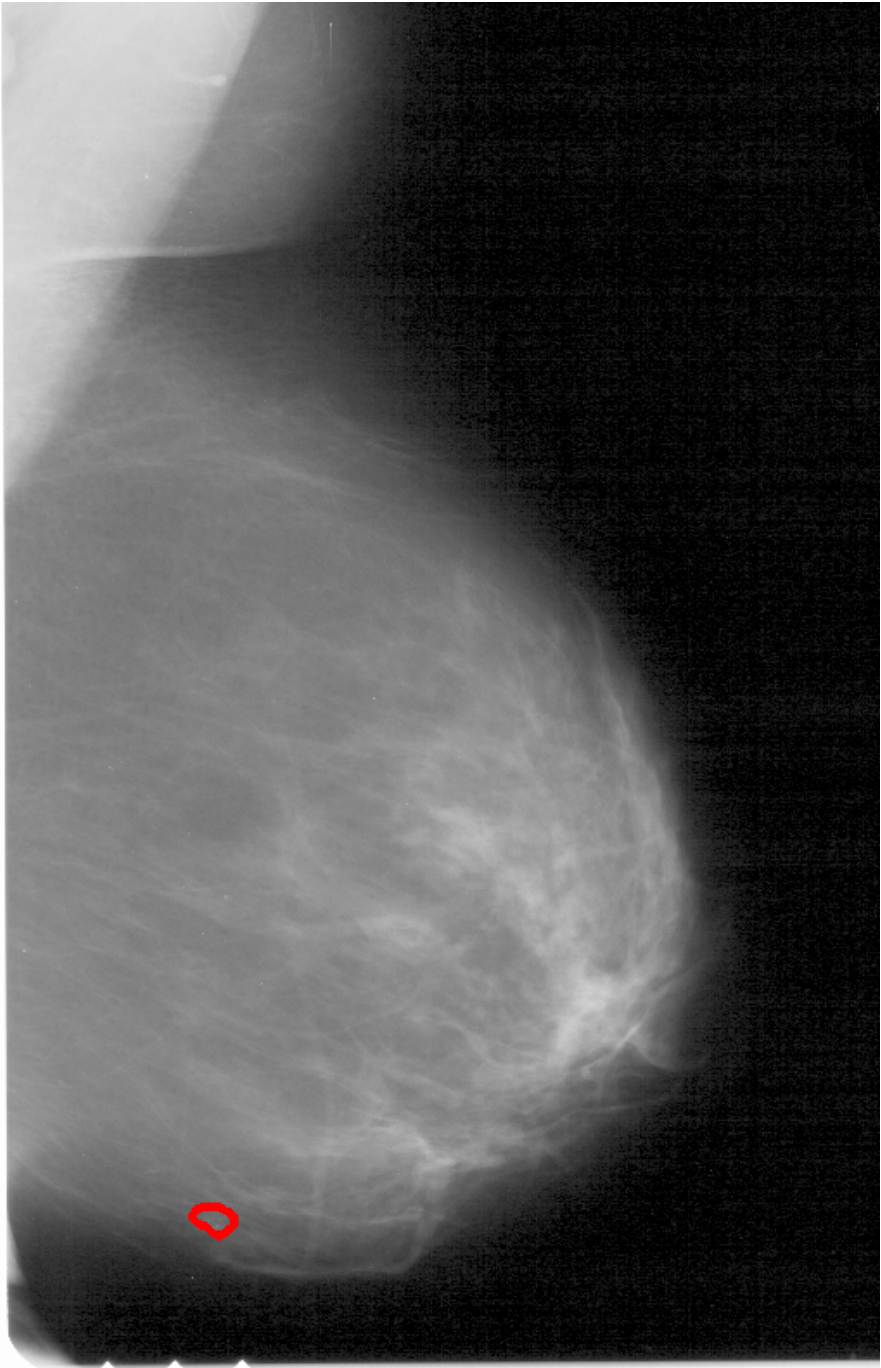


Figure A.1: An example of a DDSM data

**APPENDIX B: MICROCALCIFICATION WITH MAXIMUM α VALUE
FOR EACH ROI**

Table B.1: Microcalcification with maximum α value for each ROI

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_1259_1.mat	0.084676431	0.025240216	0.614769548	10.77197715
MC_BEN_1265_4.mat	0.347223404	0.098615428	0.490803844	6.275492896
MC_BEN_1272_2.mat	0.19975872	0.04252498	0.582975705	8.810564978
MC_BEN_1275_2.mat	0.307238554	0.128832802	0.465227005	7.278547845
MC_BEN_1280_2.mat	0.175864578	0.022197345	0.598720818	9.71375325
MC_BEN_1281_1.mat	0.237342197	0.017690047	0.458650294	6.095371704
MC_BEN_1285_1.mat	0.309546224	0.037174297	0.446486919	7.098748289
MC_BEN_1310_1.mat	0.100753438	0.060198211	0.598568803	8.525565777
MC_BEN_1315_2.mat	0.266109429	0.093868379	0.506982529	8.664136631
MC_BEN_1316_1.mat	0.18662573	0.091708504	0.495537354	8.562449088
MC_BEN_1324_1.mat	0.12187249	0.044533998	0.542428748	12.15427163
MC_BEN_1327_1.mat	0.098433517	0.023290731	0.543439737	9.419546345
MC_BEN_1328_3.mat	0.113764708	0.041656053	0.529854072	9.393040294
MC_BEN_1331_1.mat	0.10741697	0.052157479	0.58483022	8.401850817
MC_BEN_1333_1.mat	0.120269727	0.033295635	0.545248786	7.796509185
MC_BEN_1345_1.mat	0.297595852	0.178357983	0.504386403	8.347717089
MC_BEN_1352_2.mat	0.284108936	0.029671215	0.53434663	10.41572376
MC_BEN_1377_1.mat	0.04417744	0.028339126	0.550486705	8.186040098
MC_BEN_1378_1.mat	0.122091168	0.044484385	0.535612658	8.299280465
MC_BEN_1429_1.mat	0.252155155	0.187341983	0.461769349	8.254601289
MC_BEN_1438_1.mat	0.084962262	0.01535973	0.604552061	9.9835409
MC_BEN_1441_2.mat	0.162174241	0.031139942	0.571004165	8.59893698
MC_BEN_1448_5.mat	0.127118954	0.029283897	0.61757009	10.39044896
MC_BEN_1452_1.mat	0.20984267	0.062868545	0.561836721	11.12415761
MC_BEN_1458_2.mat	0.31268102	0.054139773	0.52432661	11.65550049
MC_BEN_1479_1.mat	0.187935189	0.150003775	0.376170733	3.876132326
MC_BEN_1497_1.mat	0.1776908	0.067601149	0.546764185	8.030102703

Table B.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_1513_2.mat	0.13194451	0.038010922	0.602854259	10.62193633
MC_BEN_1546_2.mat	0.116896928	0.031586494	0.589910042	8.692571634
MC_BEN_1551_2.mat	0.145059977	0.142717991	0.483688246	6.536110046
MC_BEN_1552_2.mat	0.196022898	0.086496849	0.436794415	6.898970694
MC_BEN_1561_1.mat	0.222197223	0.099320461	0.478815596	11.37333273
MC_BEN_1604_2.mat	0.282848318	0.092711355	0.504224402	8.893919578
MC_BEN_1632_1.mat	0.123430676	0.019240017	0.573980409	6.840128839
MC_BEN_1646_2.mat	0.136648818	0.039310942	0.518871612	8.350427148
MC_BEN_1648_2.mat	0.299679548	0.042217244	0.527015096	8.617010368
MC_BEN_1649_2.mat	0.211849926	0.043997684	0.537139649	5.891021974
MC_BEN_1655_2.mat	0.176511778	0.048719788	0.539456337	8.295843086
MC_BEN_1735_1.mat	0.119490763	0.075223955	0.569468042	9.770666686
MC_BEN_1736_2.mat	0.227954306	0.165696322	0.408281499	3.487132
MC_BEN_1740_1.mat	0.12047272	0.028692231	0.443489736	3.383658912
MC_BEN_1741_1.mat	0.116360315	0.057894077	0.511477163	8.145009087
MC_BEN_1743_4.mat	0.109720627	0.027649728	0.65955228	10.3803839
MC_BEN_1744_4.mat	0.298760412	0.160611279	0.554986468	8.404989483
MC_BEN_1746_2.mat	0.135882476	0.117086102	0.520447882	10.92652108
MC_BEN_1749_1.mat	0.251275217	0.096698395	0.536471361	10.77884226
MC_BEN_1751_1.mat	0.137642946	0.019064038	0.571256551	6.41187649
MC_BEN_1753_1.mat	0.161871278	0.029903771	0.544078403	7.185790994
MC_BEN_1755_1.mat	0.269785189	0.053789531	0.506523931	3.725730725
MC_BEN_1760_1.mat	0.157180432	0.031581169	0.535636749	11.72943651
MC_BEN_1762_3.mat	0.141313026	0.019141173	0.526837071	9.476811879
MC_BEN_1774_1.mat	0.140113508	0.073104531	0.571719087	8.933101838
MC_BEN_1775_2.mat	0.129098043	0.052038356	0.529923929	10.23513392
MC_BEN_1791_1.mat	0.075548868	0.034063085	0.553693435	9.984340992
MC_BEN_1806_1.mat	0.162037178	0.067946998	0.55827106	11.17646723
MC_BEN_1807_1.mat	0.119032463	0.025040852	0.530869684	8.148352477
MC_BEN_1818_1.mat	0.074053438	0.028140046	0.579897789	11.0924612
MC_BEN_1829_1.mat	0.175414282	0.050085998	0.600359615	9.452233238
MC_BEN_1839_3.mat	0.19387208	0.056848963	0.568130992	8.851765591
MC_BEN_1844_3.mat	0.211831534	0.097614139	0.572290301	10.25076383
MC_BEN_1854_2.mat	0.275745524	0.107729608	0.426754439	5.731524928

Table B.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_1859_1.mat	0.097685122	0.029189451	0.557385169	9.253884991
MC_BEN_1864_1.mat	0.289145129	0.253900115	0.390073331	3.601533865
MC_BEN_1866_3.mat	0.239783652	0.075311783	0.491325395	13.67271548
MC_BEN_1867_2.mat	0.072810784	0.027126906	0.574181373	4.601949431
MC_BEN_1868_4.mat	0.212729421	0.083208875	0.565738659	10.08918177
MC_BEN_1870_1.mat	0.157951025	0.04381759	0.53032733	9.374086889
MC_BEN_1883_2.mat	0.174341254	0.064742059	0.521634264	8.842924457
MC_BEN_1891_3.mat	0.309329762	0.097452288	0.438930814	7.402733643
MC_BEN_1909_1.mat	0.18982443	0.05064472	0.587308283	10.15049265
MC_BEN_1810_1.mat	0.208772845	0.113735428	0.508240137	7.77000038
MC_BEN_1913_1.mat	0.153849094	0.050200854	0.539014765	6.854436674
MC_BEN_1914_2.mat	0.140756371	0.025582419	0.470753774	3.9861419
MC_BEN_1919_1.mat	0.207050568	0.094576784	0.525250717	6.322383379
MC_BEN_1923_1.mat	0.15648614	0.111472902	0.531782791	7.568149171
MC_BEN_1924_1.mat	0.26052208	0.077936745	0.535047193	9.706566101
MC_BEN_1925_2.mat	0.142916184	0.099369024	0.5057077	8.706285416
MC_BEN_1926_2.mat	0.230994626	0.099597288	0.508985208	4.903648901
MC_BEN_1935_2.mat	0.122161088	0.032322241	0.568010725	7.527438287
MC_BEN_1944_2.mat	0.074539088	0.021776604	0.581924399	4.700994026
MC_BEN_1945_2.mat	0.235715368	0.052547324	0.478283253	11.95492102
MC_BEN_1949_1.mat	0.18349787	0.133491298	0.489285859	8.177304507
MC_BEN_1953_1.mat	0.148433677	0.047074708	0.489683071	9.87323803
MC_BEN_236_1.mat	0.03611096	0.026877529	0.721452799	11.65276467
MC_BEN_242_1.mat	0.215991537	0.09482873	0.547788832	11.32481955
MC_BEN_272_2.mat	0.19285309	0.04664157	0.472461752	6.626807254
MC_BEN_281_1.mat	0.256007421	0.118713061	0.437578831	7.31377138
MC_BEN_300_1.mat	0.080088734	0.030952231	0.559494298	8.241624679
MC_BEN_301_2.mat	0.122658959	0.060489579	0.53672005	9.853453993
MC_BEN_307_6.mat	0.090573327	0.02651801	0.662553259	11.07401733
MC_BEN_315_1.mat	0.275655885	0.073929006	0.483081529	8.910022167
MC_BEN_375_3.mat	0.132834731	0.036762227	0.524491058	7.367340189
MC_BEN_379_1.mat	0.087574698	0.020663597	0.545480485	9.252053437
MC_BEN_390_2.mat	0.171372115	0.050093408	0.556085569	10.84750429
MC_BEN_391_2.mat	0.264145456	0.179927615	0.496953644	11.03708282

Table B.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_400_1.mat	0.223013595	0.0537195	0.460600319	7.854228687
MC_BEN_409_1.mat	0.250726678	0.090103446	0.459862987	8.575346769
MC_BEN_412_2.mat	0.163326876	0.11976707	0.476834382	6.459242578
MC_BEN_466_1.mat	0.191607247	0.044737435	0.464235692	8.972168663
MC_BEN_476_2.mat	0.208673277	0.057665175	0.573991942	8.893155447
MC_BEN_486_1.mat	0.115452647	0.06761639	0.487405951	7.12593918
MC_BEN_486_1.mat	0.225406225	0.049678189	0.499694181	12.11182743
MC_BEN_492_1.mat	0.240111809	0.024398173	0.471701072	7.961396342
MC_BEN_500_1.mat	0.26416649	0.089350269	0.469659468	12.45963728
MC_BEN_502_2.mat	0.094701262	0.054511274	0.529356454	8.994683334
MC_BEN_508_2.mat	0.192660008	0.071574437	0.402172903	3.0905081
MC_BEN_3092_1.mat	0.045326595	0.016826897	0.611459618	10.78233669
MC_BEN_3094_3.mat	0.096328372	0.039695173	0.566121067	10.99798263
MC_BEN_3141_1.mat	0.26446823	0.062446106	0.405635645	8.861520736
MC_BEN_3145_1.mat	0.156787559	0.014927636	0.473589469	5.972793304
MC_BEN_3365_1.mat	0.161553676	0.062121053	0.553952719	9.616617034
MC_BEN_3367_1.mat	0.198938596	0.138071224	0.466385739	8.235886941
MC_BEN_3436_1.mat	0.245282993	0.124279487	0.526764818	6.488217321
MC_BEN_3437_1.mat	0.154825102	0.031369339	0.506701622	8.043157306
MC_BEN_3455_1.mat	0.151923276	0.03377004	0.606752589	11.75606809
MC_BEN_3456_2.mat	0.191694169	0.083437569	0.416514298	4.204619055
MC_BEN_3457_1.mat	0.174002525	0.042168244	0.539639772	7.210099175
MC_BEN_3459_1.mat	0.146061643	0.021862321	0.596334268	10.06187453
MC_BEN_3465_1.mat	0.093699906	0.043648452	0.670753962	11.04484382
MC_BEN_3470_1.mat	0.161012804	0.089538139	0.482766005	12.46845749
MC_BEN_3472_2.mat	0.133992435	0.042718634	0.558000465	6.340218519
MC_BEN_3473_1.mat	0.184482442	0.041751233	0.563811172	9.530185699
MC_BEN_3486_3.mat	0.178689974	0.10954331	0.505537906	5.0265508
MC_BEN_3493_1.mat	0.248624834	0.027391573	0.504882192	7.591592118
MC_BEN_3494_2.mat	0.139721654	0.029152606	0.552592905	10.10404913
MC_MAL_1133_2.mat	0.528737747	0.377447031	0.36383988	4.845661779
MC_MAL_1148_3.mat	0.33041194	0.149666687	0.469996884	11.05426209
MC_MAL_1152_4.mat	0.172003283	0.052078644	0.426732332	7.994123988
MC_MAL_1153_3.mat	0.28414292	0.083882634	0.52621936	9.143124751

Table B.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_MAL_1185_3.mat	0.112192246	0.128492554	0.467475407	9.0448637
MC_MAL_1188_3.mat	0.291342338	0.055304239	0.560161147	12.09495169
MC_MAL_1201_3.mat	0.317095561	0.089999468	0.422986739	6.240750261
MC_MAL_1212_2.mat	0.256480673	0.056049615	0.561035336	10.79214147
MC_MAL_1213_7.mat	0.124627097	0.02417126	0.509627126	6.363471119
MC_MAL_1214_6.mat	0.079253238	0.032063042	0.592798761	9.791501017
MC_MAL_1223_3.mat	0.255613256	0.052903122	0.527444142	9.879499745
MC_MAL_1235_3.mat	0.39296243	0.094585245	0.532589484	11.65540818
MC_MAL_1238_2.mat	0.484097037	0.211800168	0.41440072	5.035175176
MC_MAL_1245_2.mat	0.43324245	0.15264398	0.538230696	9.121849255
MC_MAL_1248_6.mat	0.289252978	0.040623363	0.499020452	9.075978768
MC_MAL_1250_4.mat	0.37360809	0.075499953	0.49961605	8.730505406
MC_MAL_1256_2.mat	0.304906035	0.10100377	0.445495553	10.0780595
MC_MAL_1257_3.mat	0.234096514	0.04498372	0.548822149	6.562069065
MC_MAL_1261_2.mat	0.254609044	0.147282865	0.520753742	9.871731751
MC_MAL_1489_3.mat	0.263603928	0.056305188	0.497930208	8.601244908
MC_MAL_1500_4.mat	0.116269126	0.080335843	0.537378749	10.50014809
MC_MAL_1528_3.mat	0.18436958	0.070862081	0.402003621	4.324873083
MC_MAL_1531_3.mat	0.319234481	0.087314144	0.51174632	10.82943995
MC_MAL_1585_2.mat	0.383554559	0.106952859	0.459923552	6.969219653
MC_MAL_1590_1.mat	0.311934405	0.137503952	0.441563734	6.809559505
MC_MAL_1596_3.mat	0.184663726	0.047623899	0.486958923	7.068926005
MC_MAL_1614_1.mat	0.279711636	0.185862161	0.391656876	2.370364398
MC_MAL_1637_3.mat	0.343815373	0.34637897	0.42792009	5.172230163
MC_MAL_1675_1.mat	0.453423306	0.296936482	0.400399786	6.102914113
MC_MAL_1819_6.mat	0.049790479	0.024865456	0.608561588	9.123623387
MC_MAL_1894_1.mat	0.338617962	0.353741483	0.369843643	4.051984831
MC_MAL_1897_5.mat	0.293965363	0.102611262	0.557918215	9.152596853
MC_MAL_1905_1.mat	0.363717075	0.078664382	0.505186397	11.71062071
MC_MAL_1907_2.mat	0.084295431	0.021871202	0.57131448	6.179503044
MC_MAL_4151_5.mat	0.157774791	0.118388393	0.558258221	9.230696185
MC_MAL_4117_2.mat	0.252391081	0.027172212	0.427275323	4.72104505
MC_MAL_4158_1.mat	0.272765728	0.188414977	0.393244502	4.642228102
MC_MAL_4161_2.mat	0.298070732	0.06641729	0.470328725	6.944532205

Table B.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_MAL_4182_5.mat	0.217062366	0.030990162	0.568507446	11.1376256
MC_MAL_63_4.mat	0.05078913	0.039441553	0.645653922	9.650091481
MC_MAL_87_2.mat	0.199702352	0.067467241	0.563289444	8.563738456
MC_MAL_90_2.mat	0.265606749	0.098405971	0.539460706	9.889550053
MC_MAL_96_2.mat	0.234687875	0.074800255	0.470739498	7.629193722
MC_MAL_99_2.mat	0.188015136	0.137714018	0.455260326	9.278270858
MC_MAL_106_4.mat	0.139996976	0.044309131	0.561431326	8.777875486
MC_MAL_132_3.mat	0.286655134	0.053970416	0.465514088	8.720718134
MC_MAL_167_1.mat	0.388661871	0.456851315	0.352259982	5.694313149
MC_MAL_171_3.mat	0.225700483	0.077972193	0.547883075	8.712827494
MC_MAL_309_3.mat	0.388581978	0.05315112	0.439518347	8.969793882
MC_MAL_3044_4.mat	0.141011138	0.025996265	0.556078786	7.753603423
MC_MAL_3055_5.mat	0.199965258	0.052269033	0.479480094	9.188225493
MC_MAL_3382_3.mat	0.328638051	0.122335785	0.591837158	10.63397466
MC_MAL_3389_2.mat	0.109308743	0.042350634	0.626327556	9.9927393
MC_MAL_3406_2.mat	0.357365892	0.084558158	0.436413	9.28687106
MC_MAL_3476_5.mat	0.346551973	0.097383541	0.430315119	5.791465025
MC_MAL_3498_2.mat	0.290699714	0.091543027	0.41481946	10.65937887
MC_MAL_3504_2.mat	0.472145662	0.162701336	0.504748288	9.841025799
MC_MAL_3512_5.mat	0.089739537	0.01109452	0.632236507	10.01128331

APPENDIX C: TEST RESULT OF ALL MICROCALCIFICATIONS

Table C.1: Test result of all Microcalcifications

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_1259_1.mat	0.084676431	0.025240216	0.614769548	10.77197715
MC_BEN_1265_4.mat	0.347223404	0.098615428	0.490803844	6.275492896
MC_BEN_1265_4.mat	0.297898778	0.060605516	0.457782693	6.577760302
MC_BEN_1265_4.mat	0.216795795	0.042637401	0.501735552	7.127286181
MC_BEN_1265_4.mat	0.183348459	0.020060262	0.548460946	6.591384054
MC_BEN_1272_2.mat	0.19975872	0.04252498	0.582975705	8.810564978
MC_BEN_1272_2.mat	0.168662412	0.086794622	0.560598761	9.943083386
MC_BEN_1275_2.mat	0.307238554	0.128832802	0.465227005	7.278547845
MC_BEN_1275_2.mat	0.223423099	0.031963097	0.56807436	11.63147179
MC_BEN_1280_2.mat	0.175864578	0.022197345	0.598720818	9.71375325
MC_BEN_1280_2.mat	0.158236324	0.077995207	0.584773321	8.9832727
MC_BEN_1281_1.mat	0.237342197	0.017690047	0.458650294	6.095371704
MC_BEN_1285_1.mat	0.309546224	0.037174297	0.446486919	7.098748289
MC_BEN_1310_1.mat	0.100753438	0.060198211	0.598568803	8.525565777
MC_BEN_1315_2.mat	0.266109429	0.093868379	0.506982529	8.664136631
MC_BEN_1315_2.mat	0.287394278	0.042281446	0.513034326	10.44401844
MC_BEN_1316_1.mat	0.18662573	0.091708504	0.495537354	8.562449088
MC_BEN_1324_1.mat	0.12187249	0.044533998	0.542428748	12.15427163
MC_BEN_1327_1.mat	0.098433517	0.023290731	0.543439737	9.419546345
MC_BEN_1328_3.mat	0.113764708	0.041656053	0.529854072	9.393040294
MC_BEN_1328_3.mat	0.241670388	0.162111536	0.387854206	4.274333802
MC_BEN_1328_3.mat	0.157785358	0.098004272	0.533503079	9.022604575
MC_BEN_1331_1.mat	0.10741697	0.052157479	0.58483022	8.401850817
MC_BEN_1333_1.mat	0.120269727	0.033295635	0.545248786	7.796509185
MC_BEN_1345_1.mat	0.297595852	0.178357983	0.504386403	8.347717089
MC_BEN_1352_2.mat	0.284108936	0.029671215	0.53434663	10.41572376
MC_BEN_1352_2.mat	0.073400738	0.02294978	0.492543078	7.732298033
MC_BEN_1377_1.mat	0.04417744	0.028339126	0.550486705	8.186040098
MC_BEN_1378_1.mat	0.122091168	0.044484385	0.535612658	8.299280465

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_1429_1.mat	0.252155155	0.187341983	0.461769349	8.254601289
MC_BEN_1438_1.mat	0.084962262	0.01535973	0.604552061	9.9835409
MC_BEN_1441_2.mat	0.162174241	0.031139942	0.571004165	8.59893698
MC_BEN_1441_2.mat	0.279243597	0.105341045	0.561645049	10.16309533
MC_BEN_1448_5.mat	0.127118954	0.029283897	0.61757009	10.39044896
MC_BEN_1448_5.mat	0.184722411	0.075796868	0.566136959	10.22171802
MC_BEN_1448_5.mat	0.154813213	0.054406874	0.502941041	7.959480803
MC_BEN_1448_5.mat	0.155887688	0.053570233	0.532988734	8.104517765
MC_BEN_1448_5.mat	0.295652852	0.090213412	0.517314076	7.58913176
MC_BEN_1452_1.mat	0.20984267	0.062868545	0.561836721	11.12415761
MC_BEN_1458_2.mat	0.31268102	0.054139773	0.52432661	11.65550049
MC_BEN_1458_2.mat	0.281954769	0.036392862	0.531580527	7.187885731
MC_BEN_1479_1.mat	0.187935189	0.150003775	0.376170733	3.876132326
MC_BEN_1497_1.mat	0.1776908	0.067601149	0.546764185	8.030102703
MC_BEN_1513_2.mat	0.13194451	0.038010922	0.602854259	10.62193633
MC_BEN_1513_2.mat	0.214365471	0.051067462	0.502229212	9.184008586
MC_BEN_1546_2.mat	0.116896928	0.031586494	0.589910042	8.692571634
MC_BEN_1546_2.mat	0.156773191	0.020678976	0.483978334	8.245882606
MC_BEN_1551_2.mat	0.145059977	0.142717991	0.483688246	6.536110046
MC_BEN_1551_2.mat	0.127551018	0.037996084	0.541450043	8.377847325
MC_BEN_1552_2.mat	0.196022898	0.086496849	0.436794415	6.898970694
MC_BEN_1552_2.mat	0.154094774	0.103507531	0.559176306	11.46409708
MC_BEN_1561_1.mat	0.222197223	0.099320461	0.478815596	11.37333273
MC_BEN_1604_2.mat	0.282848318	0.092711355	0.504224402	8.893919578
MC_BEN_1604_2.mat	0.207058997	0.113735076	0.487965194	7.747930085
MC_BEN_1632_1.mat	0.123430676	0.019240017	0.573980409	6.840128839
MC_BEN_1646_2.mat	0.136648818	0.039310942	0.518871612	8.350427148
MC_BEN_1646_2.mat	0.15907701	0.147039305	0.447876167	8.832799424
MC_BEN_1648_2.mat	0.299679548	0.042217244	0.527015096	8.617010368
MC_BEN_1648_2.mat	0.149953568	0.025059129	0.585679818	7.75484615
MC_BEN_1649_2.mat	0.211849926	0.043997684	0.537139649	5.891021974
MC_BEN_1649_2.mat	0.158438223	0.069128332	0.596577673	10.96006251
MC_BEN_1655_2.mat	0.176511778	0.048719788	0.539456337	8.295843086
MC_BEN_1655_2.mat	0.239845366	0.062024079	0.567465572	13.89001336

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_1735_1.mat	0.119490763	0.075223955	0.569468042	9.770666686
MC_BEN_1736_2.mat	0.227954306	0.165696322	0.408281499	3.487132
MC_BEN_1736_2.mat	0.139333386	0.043179018	0.495722497	6.009852343
MC_BEN_1740_1.mat	0.12047272	0.028692231	0.443489736	3.383658912
MC_BEN_1741_1.mat	0.116360315	0.057894077	0.511477163	8.145009087
MC_BEN_1743_4.mat	0.109720627	0.027649728	0.65955228	10.3803839
MC_BEN_1743_4.mat	0.154046789	0.022801152	0.534727501	9.537066388
MC_BEN_1743_4.mat	0.203673971	0.088027606	0.557680593	8.470288397
MC_BEN_1743_4.mat	0.183206395	0.039589007	0.520898341	9.062050715
MC_BEN_1744_4.mat	0.298760412	0.160611279	0.554986468	8.404989483
MC_BEN_1744_4.mat	0.140875512	0.044835472	0.559811991	8.591445988
MC_BEN_1744_4.mat	0.092481359	0.039419603	0.537756321	9.975493922
MC_BEN_1744_4.mat	0.19306068	0.092038621	0.560352356	8.777179664
MC_BEN_1746_2.mat	0.135882476	0.117086102	0.520447882	10.92652108
MC_BEN_1746_2.mat	0.164118188	0.053338082	0.607605035	9.350094563
MC_BEN_1749_1.mat	0.251275217	0.096698395	0.536471361	10.77884226
MC_BEN_1751_1.mat	0.137642946	0.019064038	0.571256551	6.41187649
MC_BEN_1753_1.mat	0.161871278	0.029903771	0.544078403	7.185790994
MC_BEN_1755_1.mat	0.269785189	0.053789531	0.506523931	3.725730725
MC_BEN_1760_1.mat	0.157180432	0.031581169	0.535636749	11.72943651
MC_BEN_1762_3.mat	0.141313026	0.019141173	0.526837071	9.476811879
MC_BEN_1762_3.mat	0.10822825	0.024993541	0.612515246	11.43339485
MC_BEN_1762_3.mat	0.161754961	0.067125346	0.478995082	8.766313533
MC_BEN_1774_1.mat	0.140113508	0.073104531	0.571719087	8.933101838
MC_BEN_1775_2.mat	0.129098043	0.052038356	0.529923929	10.23513392
MC_BEN_1775_2.mat	0.289002343	0.05973641	0.466124454	14.38419187
MC_BEN_1791_1.mat	0.075548868	0.034063085	0.553693435	9.984340992
MC_BEN_1806_1.mat	0.162037178	0.067946998	0.55827106	11.17646723
MC_BEN_1807_1.mat	0.119032463	0.025040852	0.530869684	8.148352477
MC_BEN_1818_1.mat	0.074053438	0.028140046	0.579897789	11.0924612
MC_BEN_1829_1.mat	0.175414282	0.050085998	0.600359615	9.452233238
MC_BEN_1839_3.mat	0.19387208	0.056848963	0.568130992	8.851765591
MC_BEN_1839_3.mat	0.140775917	0.025612741	0.628046522	8.220338289
MC_BEN_1839_3.mat	0.116204302	0.01703115	0.542380604	9.365111881

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_1844_3.mat	0.211831534	0.097614139	0.572290301	10.25076383
MC_BEN_1844_3.mat	0.139177116	0.132136454	0.462039811	6.545781014
MC_BEN_1844_3.mat	0.150970189	0.080242697	0.52561792	12.70921559
MC_BEN_1854_2.mat	0.275745524	0.107729608	0.426754439	5.731524928
MC_BEN_1854_2.mat	0.246715265	0.053511034	0.504672361	12.95686846
MC_BEN_1859_1.mat	0.097685122	0.029189451	0.557385169	9.253884991
MC_BEN_1864_1.mat	0.289145129	0.253900115	0.390073331	3.601533865
MC_BEN_1866_3.mat	0.239783652	0.075311783	0.491325395	13.67271548
MC_BEN_1866_3.mat	0.127563966	0.034854475	0.525734293	7.824421309
MC_BEN_1866_3.mat	0.163882378	0.168122627	0.516214383	11.68083524
MC_BEN_1867_2.mat	0.072810784	0.027126906	0.574181373	4.601949431
MC_BEN_1867_2.mat	0.158980857	0.065722699	0.539673904	12.30758983
MC_BEN_1868_4.mat	0.212729421	0.083208875	0.565738659	10.08918177
MC_BEN_1868_4.mat	0.103591522	0.031013346	0.582783838	8.520153259
MC_BEN_1868_4.mat	0.167698655	0.064594591	0.509318149	9.392178771
MC_BEN_1868_4.mat	0.23394732	0.07084572	0.539334529	12.83632261
MC_BEN_1870_1.mat	0.157951025	0.04381759	0.53032733	9.374086889
MC_BEN_1883_2.mat	0.174341254	0.064742059	0.521634264	8.842924457
MC_BEN_1883_2.mat	0.168211836	0.060707107	0.553070718	6.912239378
MC_BEN_1891_3.mat	0.309329762	0.097452288	0.438930814	7.402733643
MC_BEN_1891_3.mat	0.280132051	0.089097766	0.463254453	6.63288486
MC_BEN_1891_3.mat	0.200447058	0.090514992	0.394159668	3.273168413
MC_BEN_1909_1.mat	0.18982443	0.05064472	0.587308283	10.15049265
MC_BEN_1810_1.mat	0.208772845	0.113735428	0.508240137	7.77000038
MC_BEN_1913_1.mat	0.153849094	0.050200854	0.539014765	6.854436674
MC_BEN_1914_2.mat	0.140756371	0.025582419	0.470753774	3.9861419
MC_BEN_1914_2.mat	0.207431444	0.082145525	0.54420566	4.820228797
MC_BEN_1919_1.mat	0.207050568	0.094576784	0.525250717	6.322383379
MC_BEN_1923_1.mat	0.15648614	0.111472902	0.531782791	7.568149171
MC_BEN_1924_1.mat	0.26052208	0.077936745	0.535047193	9.706566101
MC_BEN_1925_2.mat	0.142916184	0.099369024	0.5057077	8.706285416
MC_BEN_1925_2.mat	0.226849494	0.092693502	0.327806206	1.704884918
MC_BEN_1926_2.mat	0.230994626	0.099597288	0.508985208	4.903648901
MC_BEN_1926_2.mat	0.137058478	0.038402301	0.555504532	4.884648204

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_1935_2.mat	0.122161088	0.032322241	0.568010725	7.527438287
MC_BEN_1935_2.mat	0.176768781	0.05336069	0.523683099	10.05813958
MC_BEN_1944_2.mat	0.074539088	0.021776604	0.581924399	4.700994026
MC_BEN_1944_2.mat	0.225042001	0.028798321	0.561924346	6.657550062
MC_BEN_1945_2.mat	0.235715368	0.052547324	0.478283253	11.95492102
MC_BEN_1945_2.mat	0.25563091	0.063607192	0.433109195	7.273062918
MC_BEN_1949_1.mat	0.18349787	0.133491298	0.489285859	8.177304507
MC_BEN_1953_1.mat	0.148433677	0.047074708	0.489683071	9.87323803
MC_BEN_236_1.mat	0.03611096	0.026877529	0.721452799	11.65276467
MC_BEN_242_1.mat	0.215991537	0.09482873	0.547788832	11.32481955
MC_BEN_272_2.mat	0.19285309	0.04664157	0.472461752	6.626807254
MC_BEN_272_2.mat	0.133565826	0.058062166	0.415959654	4.980920643
MC_BEN_281_1.mat	0.256007421	0.118713061	0.437578831	7.31377138
MC_BEN_300_1.mat	0.080088734	0.030952231	0.559494298	8.241624679
MC_BEN_301_2.mat	0.122658959	0.060489579	0.53672005	9.853453993
MC_BEN_301_2.mat	0.122658959	0.060489579	0.53672005	9.853453993
MC_BEN_307_6.mat	0.090573327	0.02651801	0.662553259	11.07401733
MC_BEN_307_6.mat	0.091385275	0.036510017	0.588151702	11.20120709
MC_BEN_307_6.mat	0.122065266	0.065240284	0.554541442	10.35081242
MC_BEN_307_6.mat	0.184919261	0.039458613	0.5415229	9.699468874
MC_BEN_315_1.mat	0.275655885	0.073929006	0.483081529	8.910022167
MC_BEN_375_3.mat	0.132834731	0.036762227	0.524491058	7.367340189
MC_BEN_375_3.mat	0.218686562	0.063129618	0.523975958	10.63535362
MC_BEN_375_3.mat	0.197721243	0.048412198	0.557123438	10.76963788
MC_BEN_379_1.mat	0.087574698	0.020663597	0.545480485	9.252053437
MC_BEN_390_2.mat	0.171372115	0.050093408	0.556085569	10.84750429
MC_BEN_390_2.mat	0.190459437	0.040789942	0.551022548	9.453572471
MC_BEN_391_2.mat	0.264145456	0.179927615	0.496953644	11.03708282
MC_BEN_391_2.mat	0.186536385	0.046829194	0.543529582	10.43013586
MC_BEN_400_1.mat	0.223013595	0.0537195	0.460600319	7.854228687
MC_BEN_409_1.mat	0.250726678	0.090103446	0.459862987	8.575346769
MC_BEN_412_2.mat	0.163326876	0.11976707	0.476834382	6.459242578
MC_BEN_412_2.mat	0.200445295	0.073989382	0.459862296	10.12313383
MC_BEN_466_1.mat	0.191607247	0.044737435	0.464235692	8.972168663

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_476_2.mat	0.208673277	0.057665175	0.573991942	8.893155447
MC_BEN_476_2.mat	0.24646867	0.096153315	0.472533011	5.220144046
MC_BEN_486_1.mat	0.115452647	0.06761639	0.487405951	7.12593918
MC_BEN_486_1.mat	0.225406225	0.049678189	0.499694181	12.11182743
MC_BEN_492_1.mat	0.240111809	0.024398173	0.471701072	7.961396342
MC_BEN_500_1.mat	0.26416649	0.089350269	0.469659468	12.45963728
MC_BEN_502_2.mat	0.094701262	0.054511274	0.529356454	8.994683334
MC_BEN_502_2.mat	0.21031948	0.083684518	0.521463639	11.10729399
MC_BEN_508_2.mat	0.192660008	0.071574437	0.402172903	3.0905081
MC_BEN_508_2.mat	0.248606286	0.191414641	0.344394973	3.798421303
MC_BEN_3092_1.mat	0.045326595	0.016826897	0.611459618	10.78233669
MC_BEN_3094_3.mat	0.096328372	0.039695173	0.566121067	10.99798263
MC_BEN_3094_3.mat	0.13701773	0.059576101	0.511834644	9.420967303
MC_BEN_3094_3.mat	0.227977324	0.172388719	0.432564591	6.727420425
MC_BEN_3141_1.mat	0.26446823	0.062446106	0.405635645	8.861520736
MC_BEN_3145_1.mat	0.156787559	0.014927636	0.473589469	5.972793304
MC_BEN_3365_1.mat	0.161553676	0.062121053	0.553952719	9.616617034
MC_BEN_3367_1.mat	0.198938596	0.138071224	0.466385739	8.235886941
MC_BEN_3436_1.mat	0.245282993	0.124279487	0.526764818	6.488217321
MC_BEN_3437_1.mat	0.154825102	0.031369339	0.506701622	8.043157306
MC_BEN_3455_1.mat	0.151923276	0.03377004	0.606752589	11.75606809
MC_BEN_3456_2.mat	0.191694169	0.083437569	0.416514298	4.204619055
MC_BEN_3457_1.mat	0.174002525	0.042168244	0.539639772	7.210099175
MC_BEN_3459_1.mat	0.146061643	0.021862321	0.596334268	10.06187453
MC_BEN_3465_1.mat	0.093699906	0.043648452	0.670753962	11.04484382
MC_BEN_3470_1.mat	0.161012804	0.089538139	0.482766005	12.46845749
MC_BEN_3472_2.mat	0.133992435	0.042718634	0.558000465	6.340218519
MC_BEN_3472_2.mat	0.233406192	0.192973426	0.447272752	7.373999743
MC_BEN_3473_1.mat	0.184482442	0.041751233	0.563811172	9.530185699
MC_BEN_3486_3.mat	0.178689974	0.10954331	0.505537906	5.0265508
MC_BEN_3486_3.mat	0.154567397	0.108149977	0.542109841	11.04708078
MC_BEN_3486_3.mat	0.283103556	0.110944304	0.501304952	12.15268346
MC_BEN_3493_1.mat	0.248624834	0.027391573	0.504882192	7.591592118
MC_BEN_3494_2.mat	0.139721654	0.029152606	0.552592905	10.10404913

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_BEN_3494_2.mat	0.155505113	0.034026408	0.492395738	10.66144207
MC_MAL_1133_2.mat	0.528737747	0.377447031	0.36383988	4.845661779
MC_MAL_1133_2.mat	0.345500653	0.088929271	0.439578153	12.94972812
MC_MAL_1148_3.mat	0.33041194	0.149666687	0.469996884	11.05426209
MC_MAL_1148_3.mat	0.282804711	0.151408563	0.481554818	8.532901089
MC_MAL_1148_3.mat	0.181621259	0.064488477	0.508974985	6.956158918
MC_MAL_1152_4.mat	0.172003283	0.052078644	0.426732332	7.994123988
MC_MAL_1152_4.mat	0.216414992	0.10098766	0.432927446	7.077399794
MC_MAL_1152_4.mat	0.455556123	0.078908976	0.430316652	7.60142201
MC_MAL_1152_4.mat	0.222613356	0.023175378	0.564635592	7.180828656
MC_MAL_1153_3.mat	0.28414292	0.083882634	0.52621936	9.143124751
MC_MAL_1153_3.mat	0.148640108	0.056693612	0.477384507	6.936419176
MC_MAL_1185_3.mat	0.112192246	0.128492554	0.467475407	9.0448637
MC_MAL_1185_3.mat	0.191160486	0.11644072	0.5612425	9.041645597
MC_MAL_1185_3.mat	0.422788998	0.060199006	0.536082378	9.744836693
MC_MAL_1188_3.mat	0.291342338	0.055304239	0.560161147	12.09495169
MC_MAL_1188_3.mat	0.355078026	0.191564467	0.522751453	10.92719035
MC_MAL_1188_3.mat	0.319565169	0.063210004	0.570607285	10.94244664
MC_MAL_1201_3.mat	0.317095561	0.089999468	0.422986739	6.240750261
MC_MAL_1201_3.mat	0.237329422	0.103454395	0.428335636	7.023826361
MC_MAL_1201_3.mat	0.12478339	0.05777666	0.539548369	6.745810699
MC_MAL_1212_2.mat	0.256480673	0.056049615	0.561035336	10.79214147
MC_MAL_1212_2.mat	0.207005331	0.056406896	0.493295602	11.56877473
MC_MAL_1213_7.mat	0.124627097	0.02417126	0.509627126	6.363471119
MC_MAL_1213_7.mat	0.17518174	0.074580629	0.52457311	9.317780736
MC_MAL_1213_7.mat	0.451484839	0.140444439	0.469012625	7.66219232
MC_MAL_1213_7.mat	0.209321493	0.0501448	0.425808854	8.441036208
MC_MAL_1213_7.mat	0.284478239	0.076442209	0.472535592	8.233720437
MC_MAL_1213_7.mat	0.268503243	0.053629271	0.450112581	6.541356035
MC_MAL_1213_7.mat	0.375283767	0.10293157	0.372789888	2.975391114
MC_MAL_1214_6.mat	0.079253238	0.032063042	0.592798761	9.791501017
MC_MAL_1214_6.mat	0.39059576	0.143260547	0.44571901	7.0591608
MC_MAL_1214_6.mat	0.339051086	0.09554589	0.497510121	10.09102722
MC_MAL_1214_6.mat	0.103350291	0.03460591	0.591183777	9.394354864

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_MAL_1214_6.mat	0.19930135	0.078774046	0.519117524	8.414158555
MC_MAL_1214_6.mat	0.36603128	0.127318583	0.40003035	4.061326333
MC_MAL_1223_3.mat	0.255613256	0.052903122	0.527444142	9.879499745
MC_MAL_1223_3.mat	0.235853133	0.248806213	0.403156396	4.919354882
MC_MAL_1235_3.mat	0.39296243	0.094585245	0.532589484	11.65540818
MC_MAL_1235_3.mat	0.208009425	0.079584351	0.571023519	9.824522933
MC_MAL_1238_2.mat	0.484097037	0.211800168	0.41440072	5.035175176
MC_MAL_1238_2.mat	0.20074468	0.029757436	0.464596509	8.449023035
MC_MAL_1245_2.mat	0.43324245	0.15264398	0.538230696	9.121849255
MC_MAL_1245_2.mat	0.28321241	0.042379796	0.440460067	7.581632299
MC_MAL_1248_6.mat	0.289252978	0.040623363	0.499020452	9.075978768
MC_MAL_1248_6.mat	0.269235083	0.091200075	0.490501948	7.75839403
MC_MAL_1248_6.mat	0.080673041	0.043435079	0.513082354	8.336028628
MC_MAL_1248_6.mat	0.19290129	0.031510256	0.555956459	10.3854849
MC_MAL_1248_6.mat	0.086438382	0.059918017	0.540071163	8.506924567
MC_MAL_1248_6.mat	0.361972944	0.119994061	0.537285735	10.86065139
MC_MAL_1250_4.mat	0.37360809	0.075499953	0.49961605	8.730505406
MC_MAL_1250_4.mat	0.165665193	0.031474468	0.550206476	6.496065785
MC_MAL_1250_4.mat	0.253827278	0.101299899	0.461560265	7.112848874
MC_MAL_1250_4.mat	0.207104177	0.077034705	0.495977236	6.776767741
MC_MAL_1256_2.mat	0.304906035	0.10100377	0.445495553	10.0780595
MC_MAL_1256_2.mat	0.414237226	0.10275239	0.4166295	4.390579975
MC_MAL_1257_3.mat	0.234096514	0.04498372	0.548822149	6.562069065
MC_MAL_1257_3.mat	0.528834096	0.279729819	0.44030754	6.955589185
MC_MAL_1261_2.mat	0.254609044	0.147282865	0.520753742	9.871731751
MC_MAL_1261_2.mat	0.169100619	0.045251288	0.560550804	10.27402574
MC_MAL_1489_3.mat	0.263603928	0.056305188	0.497930208	8.601244908
MC_MAL_1489_3.mat	0.281680512	0.104564151	0.471713332	8.635614903
MC_MAL_1489_3.mat	0.526367163	0.152104016	0.457677954	6.804866281
MC_MAL_1500_4.mat	0.116269126	0.080335843	0.537378749	10.50014809
MC_MAL_1500_4.mat	0.456465467	0.161559187	0.490870772	8.679624401
MC_MAL_1500_4.mat	0.0748728	0.07290368	0.577239013	9.202154937
MC_MAL_1500_4.mat	0.254405515	0.093711326	0.414603428	4.981200977
MC_MAL_1528_3.mat	0.18436958	0.070862081	0.402003621	4.324873083

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_MAL_1528_3.mat	0.306801029	0.058848948	0.409957973	4.200789478
MC_MAL_1528_3.mat	0.308611533	0.133404105	0.43596188	10.10027633
MC_MAL_1531_3.mat	0.319234481	0.087314144	0.51174632	10.82943995
MC_MAL_1531_3.mat	0.152708705	0.052453178	0.532407278	11.36568894
MC_MAL_1531_3.mat	0.078910016	0.052493624	0.584414918	13.04077846
MC_MAL_1585_2.mat	0.383554559	0.106952859	0.459923552	6.969219653
MC_MAL_1585_2.mat	0.237802545	0.045428447	0.505105518	9.935222955
MC_MAL_1590_1.mat	0.311934405	0.137503952	0.441563734	6.809559505
MC_MAL_1596_3.mat	0.184663726	0.047623899	0.486958923	7.068926005
MC_MAL_1596_3.mat	0.709381311	0.243929298	0.398863283	5.766166333
MC_MAL_1596_3.mat	0.122822974	0.047556711	0.532254288	9.638077571
MC_MAL_1596_3.mat	0.312693951	0.157515141	0.385302111	4.971933268
MC_MAL_1614_1.mat	0.279711636	0.185862161	0.391656876	2.370364398
MC_MAL_1637_3.mat	0.343815373	0.34637897	0.42792009	5.172230163
MC_MAL_1637_3.mat	0.111443195	0.129532409	0.447270004	6.331248349
MC_MAL_1637_3.mat	0.187388839	0.072121916	0.584937729	9.959543231
MC_MAL_1675_1.mat	0.453423306	0.296936482	0.400399786	6.102914113
MC_MAL_1819_6.mat	0.049790479	0.024865456	0.608561588	9.123623387
MC_MAL_1819_6.mat	0.268159321	0.095789079	0.549391041	7.730060595
MC_MAL_1819_6.mat	0.082978846	0.060576405	0.591204488	9.290962262
MC_MAL_1819_6.mat	0.096210538	0.033185264	0.636884397	11.00212499
MC_MAL_1819_6.mat	0.109517805	0.032407344	0.609691765	8.538077718
MC_MAL_1819_6.mat	0.239905213	0.083221267	0.522182459	10.20360406
MC_MAL_1894_1.mat	0.338617962	0.353741483	0.369843643	4.051984831
MC_MAL_1897_5.mat	0.293965363	0.102611262	0.557918215	9.152596853
MC_MAL_1897_5.mat	0.302933296	0.096897907	0.470096906	8.66638869
MC_MAL_1897_5.mat	0.315450765	0.095325874	0.417070176	6.616819331
MC_MAL_1897_5.mat	0.081683997	0.018059487	0.582050726	3.972919821
MC_MAL_1897_5.mat	0.163955992	0.049746699	0.573113051	6.893859386
MC_MAL_1905_1.mat	0.363717075	0.078664382	0.505186397	11.71062071
MC_MAL_1907_2.mat	0.084295431	0.021871202	0.57131448	6.179503044
MC_MAL_1907_2.mat	0.312295358	0.121419954	0.399893971	9.557157628
MC_MAL_4151_5.mat	0.157774791	0.118388393	0.558258221	9.230696185
MC_MAL_4151_5.mat	0.20612677	0.062788457	0.47223981	9.564674829

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_MAL_4151_5.mat	0.280896199	0.060216824	0.483313692	10.0384325
MC_MAL_4151_5.mat	0.10782223	0.060044194	0.57394912	8.446726407
MC_MAL_4151_5.mat	0.16972228	0.081322371	0.580107609	10.20379928
MC_MAL_4117_2.mat	0.252391081	0.027172212	0.427275323	4.72104505
MC_MAL_4117_2.mat	0.201221691	0.042755448	0.613683593	10.58656446
MC_MAL_4158_1.mat	0.272765728	0.188414977	0.393244502	4.642228102
MC_MAL_4161_2.mat	0.298070732	0.06641729	0.470328725	6.944532205
MC_MAL_4161_2.mat	0.539178946	0.081682414	0.531691923	8.6697808
MC_MAL_4182_5.mat	0.217062366	0.030990162	0.568507446	11.1376256
MC_MAL_4182_5.mat	0.346165367	0.077566573	0.409462604	5.743061337
MC_MAL_4182_5.mat	0.151828105	0.075565922	0.539607809	10.04242461
MC_MAL_4182_5.mat	0.280567924	0.07313492	0.512680973	8.846371331
MC_MAL_4182_5.mat	0.139014811	0.052322337	0.535740904	10.66775184
MC_MAL_63_4.mat	0.05078913	0.039441553	0.645653922	9.650091481
MC_MAL_63_4.mat	0.069732072	0.01350984	0.625159677	10.48653801
MC_MAL_63_4.mat	0.075639336	0.073502706	0.605787149	10.85134788
MC_MAL_63_4.mat	0.322387299	0.059693762	0.581634993	12.70595006
MC_MAL_87_2.mat	0.199702352	0.067467241	0.563289444	8.563738456
MC_MAL_87_2.mat	0.361577435	0.064740406	0.467311351	11.75524669
MC_MAL_90_2.mat	0.265606749	0.098405971	0.539460706	9.889550053
MC_MAL_90_2.mat	0.092386819	0.031623253	0.574672448	10.54962524
MC_MAL_96_2.mat	0.234687875	0.074800255	0.470739498	7.629193722
MC_MAL_96_2.mat	0.421763241	0.16296421	0.415408277	7.070163511
MC_MAL_99_2.mat	0.188015136	0.137714018	0.455260326	9.278270858
MC_MAL_99_2.mat	0.503667296	0.22729483	0.378263597	5.786918791
MC_MAL_106_4.mat	0.139996976	0.044309131	0.561431326	8.777875486
MC_MAL_106_4.mat	0.468983351	0.127951778	0.500079687	7.853323192
MC_MAL_106_4.mat	0.251099422	0.071029401	0.545608669	10.77008865
MC_MAL_106_4.mat	0.20445071	0.060898494	0.454290225	5.98186467
MC_MAL_132_3.mat	0.286655134	0.053970416	0.465514088	8.720718134
MC_MAL_132_3.mat	0.211367938	0.104350373	0.551084621	6.888984272
MC_MAL_132_3.mat	0.111090457	0.060799648	0.541949396	10.65605139
MC_MAL_167_1.mat	0.388661871	0.456851315	0.352259982	5.694313149
MC_MAL_171_3.mat	0.225700483	0.077972193	0.547883075	8.712827494

Table C.1 – Continued

DDSM case	α	Fourier	Moment	Compactness
MC_MAL_171_3.mat	0.318132475	0.040758229	0.449842812	8.596802359
MC_MAL_171_3.mat	0.117018416	0.028821597	0.480048164	5.989701789
MC_MAL_309_3.mat	0.388581978	0.053151112	0.439518347	8.969793882
MC_MAL_309_3.mat	0.562154695	0.412860179	0.370874682	6.272691358
MC_MAL_309_3.mat	0.294832544	0.050372997	0.470699246	9.346801831
MC_MAL_3044_4.mat	0.141011138	0.025996265	0.556078786	7.753603423
MC_MAL_3044_4.mat	0.200597901	0.018457294	0.53218646	9.261168864
MC_MAL_3044_4.mat	0.660521239	0.224964415	0.374617758	5.811162849
MC_MAL_3044_4.mat	0.459873521	0.153684258	0.345108553	5.196387849
MC_MAL_3055_5.mat	0.199965258	0.052269033	0.479480094	9.188225493
MC_MAL_3055_5.mat	0.578240001	0.315239301	0.38008487	5.001795599
MC_MAL_3055_5.mat	0.171023292	0.034932694	0.475983358	6.74570752
MC_MAL_3055_5.mat	0.073506484	0.026655601	0.501392043	8.025074095
MC_MAL_3382_3.mat	0.328638051	0.122335785	0.591837158	10.63397466
MC_MAL_3382_3.mat	0.165001562	0.036242978	0.597874045	11.4536211
MC_MAL_3382_3.mat	0.199396347	0.060705454	0.564609708	11.14205273
MC_MAL_3389_2.mat	0.109308743	0.042350634	0.626327556	9.9927393
MC_MAL_3389_2.mat	0.26012133	0.032001708	0.493259011	8.484919629
MC_MAL_3406_2.mat	0.357365892	0.084558158	0.436413	9.28687106
MC_MAL_3406_2.mat	0.213313147	0.100720388	0.567779043	7.325314436
MC_MAL_3476_5.mat	0.346551973	0.097383541	0.430315119	5.791465025
MC_MAL_3476_5.mat	0.364124272	0.098968699	0.421164515	6.995450454
MC_MAL_3476_5.mat	0.214231009	0.160554904	0.422500669	7.62657427
MC_MAL_3476_5.mat	0.246271404	0.114801648	0.389018979	4.873453616
MC_MAL_3476_5.mat	0.267247456	0.123192648	0.428715456	6.47474213
MC_MAL_3498_2.mat	0.290699714	0.091543027	0.41481946	10.65937887
MC_MAL_3498_2.mat	0.238030455	0.085037123	0.401910364	4.749914547
MC_MAL_3504_2.mat	0.472145662	0.162701336	0.504748288	9.841025799
MC_MAL_3504_2.mat	0.151620411	0.065511853	0.578661906	12.03739035
MC_MAL_3512_5.mat	0.089739537	0.01109452	0.632236507	10.01128331
MC_MAL_3512_5.mat	0.194881775	0.068226344	0.472766946	7.527378041
MC_MAL_3512_5.mat	0.54132829	0.108928591	0.458065648	12.42070913
MC_MAL_3512_5.mat	0.227827526	0.037475408	0.473564387	7.832895435

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