CHAPTER 4

RESULTS AND DISCUSSION

In this chapter, the characteristics of normal and abnormal breast thermal images are discussed. The results of denoising and segmentation of breast tissues are analyzed. The performance of various segmentation methods is evaluated by comparing against GT images. The significance of the extracted features in differentiating normal and varied pathological conditions is presented.

4.1 REPRESENTATIVE BREAST THERMAL IMAGES

The representative frontal normal breast thermal images are shown in Figure 4.1 (a). These images reflect the symmetrical thermal pattern distributions. The corresponding colour coded images are shown in Figure 4.1 (b). The thermal images exhibit breast regions with varying shape, size and density. These images are found to have weak edges due to their low contrast nature. Hence, the boundaries near lower breast regions and infra mammary folds are not distinguishable from background tissues. The thermal images have different distribution characteristics for different classes of images such as normal, benign and malignant. These differences are often subtle and apparent only to a trained eye. The representative abnormal thermal images and the corresponding color coded images of varied pathological conditions namely, carcinoma, fibroadenoma, nodule and cyst are shown in Figures 4.2-4.5 respectively.
Figure 4.1 Representative (a) gray scale and (b) color coded normal breast thermal images
Figure 4.2 Representative (a-b) gray scale and (c-d) color coded abnormal thermal images of breasts with carcinoma

Figure 4.3 Representative (a-b) gray scale and (c-d) color coded abnormal thermal images of breasts with fibroadenoma
Figure 4.4 Representative (a-b) gray scale and (c-d) color coded abnormal thermal images of breast with nodule

Figure 4.5 Representative (a-b) gray scale and (c-d) color coded abnormal thermal images of breast with cyst
The gray scale thermal image of the subject having carcinoma in left breast region and its corresponding color coded image are shown in Figures 4.2 (a) and (c) respectively. The gray scale thermal image of the subject having carcinoma in right breast region and its corresponding color coded image are shown in Figures 4.2 (b) and (d) respectively. The presence of carcinoma is observed as a relatively brighter spot compared to other regions resulting in asymmetry in thermal distribution. This is mainly due to increased metabolic activities. The degree of asymmetry depends on the growth rate of abnormal tissues and their associated metabolic activities.

The gray scale thermal images of the subjects having fibroadenoma in right breast regions and their corresponding color coded images are shown in Figure 4.3. This non-cancerous abnormal condition has higher rate of metabolic activity when compared to healthy breast tissues and hence it is seen as a relatively brighter region in the image. The appearance of bright spot depends on the size, depth, position, metabolic activity and severity of abnormal tissues. Compared to carcinoma, fibroadenoma has lower metabolic rate, but it is still seen as a bright spot, because the image is represented as a relative temperature map.

The gray scale thermal images of the subjects having nodule in the right breast regions and their corresponding color coded images are shown in Figure 4.4. The nodule is non-cancerous fluid filled sac that has no metabolic activity. Due to this, it is seen as a cold spot compared to normal tissues. Figure 4.5 shows the thermal image of the subjects having cyst in the left breast regions. Like nodule, a cyst is also non-cancerous tissue seen as cold spot. Hence, it is difficult to differentiate cold spot caused by non-cancerous tissue and normal tissue having comparatively lower metabolic activity.
4.2 ANALYSIS OF PERFORMANCE OF DENOISING METHODS

The breast thermal images are subjected to block matching and 3D filtering and OWTSURELET denoising methods. The signal to noise ratio based performance analysis is presented.

4.2.1 Block Matching and 3D Filtering Method

The representative raw images, corresponding BM3D denoised and noise images are shown in Figure 4.6. Noise image that is generated as the difference between the raw image and its denoised version shows the noise removed by the algorithm. The denoised images appear to be smooth and noise images are found to have subtle edge details.

<table>
<thead>
<tr>
<th>Raw Image</th>
<th>Denoised Image</th>
<th>Noise Image</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1" alt="Raw Image" /></td>
<td><img src="image2" alt="Denoised Image" /></td>
<td><img src="image3" alt="Noise Image" /></td>
</tr>
<tr>
<td><img src="image4" alt="Raw Image" /></td>
<td><img src="image5" alt="Denoised Image" /></td>
<td><img src="image6" alt="Noise Image" /></td>
</tr>
</tbody>
</table>

**Figure 4.6 Denoising results using BM3D filtering**

BM3D method is able to remove the noise effectively in homogenous areas. This method fails to retain fine structural details as it
could not deliver highly sparse representation for sharp and curved edges. The noise images consist of noise as well as image details. When the noise level is large, block matching is not reliable resulting in less sparser representation in transform domain. It tends to give poor visual results when exposed to micro textured zones. It also reduces the contrast of denoised images and suppresses important edge information near infra mammary folds as shown in Figure 4.6.

**Figure 4.7** Variations of estimated SNR values of raw and BM3D denoised images for normal subjects

The variations of SNR values for raw and denoised images of normal subjects are shown in Figure 4.7. SNR values of raw images are scattered due to the presence of random noises. Denoised images illustrate a consistent improvement in their SNR values when compared to raw images. This shows that the images are smoothed properly. BM3D algorithm is able to improve SNR value by 27.22 dB.
Figure 4.8 Variations of estimated SNR values of raw and BM3D denoised images for carcinoma subjects

Figure 4.9 Variations of estimated SNR values of raw and BM3D denoised images for subjects with nodule
The variations of SNR values for raw and denoised images for different pathological conditions are shown in Figure 4.8-4.10. SNR values of raw images are highly scattered in carcinoma case which may be due to the presence of random noises. The improved SNR values of denoised images indicate that this algorithm is capable of handling varied degree of noise present in raw images. BM3D algorithm is able to improve SNR value by 27.19 dB.

The SNR values of raw and denoised images of subjects with nodule are less scattered when compared to other pathological conditions. The SNR values of corresponding denoised images are increased by an average value of 30.63 dB. Similar results are observed for fibroadenoma and cyst. BM3D algorithm is able to improve SNR values of denoised images of subjects with fibroadenoma and cyst by 26.24 and 32 dB respectively. However, this denoising method tends to lose important edge information corresponding to variations of thermal patterns. The mean and standard
deviation of SNR values for the raw and denoised images of normal and abnormal subjects are presented in Table 4.1.

**Table 4.1  Statistical values of SNR of raw and BM3D denoised normal and different pathological breast tissues**

<table>
<thead>
<tr>
<th>Type of image</th>
<th>Mean ± Standard deviation of SNR(dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Raw</td>
</tr>
<tr>
<td>Normal</td>
<td>33.24 ± 7.04</td>
</tr>
<tr>
<td>Carcinoma</td>
<td>33.82 ± 7.21</td>
</tr>
<tr>
<td>Nodule</td>
<td>30.98 ± 3.67</td>
</tr>
<tr>
<td>Fibroadenoma</td>
<td>35.21 ± 8.78</td>
</tr>
<tr>
<td>Cyst</td>
<td>29.63 ± 2.81</td>
</tr>
</tbody>
</table>

The average SNR values of denoised images are high for normal and different pathological conditions. The standard deviation values of SNR of raw images are high compared to that of denoised images. This is due to the presence of random nature of noise distribution across images. The standard deviation values of SNR of raw images are high for carcinoma and fibroadenoma which is mainly due to increased metabolic activities. The standard deviation values of SNR of raw images are low for nodule and cyst which is mainly due to lesser metabolic activities compared to normal tissues. Despite the variations in SNR values of raw images, the SNR values of denoised images of normal and pathological conditions are found to be consistent.

**4.2.2  OWTSURELET Method**

The representative raw images, corresponding OWTSURELET denoised and noise images are shown in Figure 4.11. OWTSURELET method
removes the noise and retains the edges without compromising on fine structural details of the images.

![Raw Image | Denoised Image | Noise Image](image)

**Figure 4.11 Denoising results using OWTSURELET**

The breast regions are smoothed such that the necessary details in the image are preserved as shown in Figure 4.11. The noise images have negligible edge details. Edge information near lower breast boundaries and infra mammary folds are preserved in the denoised images. This performance is observed in all images considered in this work. The estimated SNR values of raw and denoised images are used to evaluate the performance of denoising algorithm and are shown as scatter plot representation in Figures 4.12 – 4.15.

The variations of SNR values for raw images of normal subjects shown in Figure 4.13 are scattered due to the presence of random noises.
Figure 4.12 Variations of estimated SNR values of raw and OWTSURELET denoised images for normal subjects

Figure 4.13 Variations of estimated SNR values of raw and OWTSURELET denoised images for carcinoma subjects
Figure 4.14 Variations of estimated SNR values of raw and OWTSURELET denoised images for subjects with nodule

Figure 4.15 Variations of estimated SNR values of raw and OWTSURELET denoised images for fibroadenoma subjects
These values are clustered and illustrate a consistent improvement for denoised images. The average SNR values of denoised images are improved by 38.7 dB. OWTSURELET algorithm achieves high SNR improvement and visual quality improvement. This shows that the images are smoothed properly without compromising edge information loss.

The variations of SNR values for raw and denoised images of carcinoma subjects are shown in Figure 4.13. The randomness in SNR values of raw images is reasonably addressed by removing the noise component effectively using OWTSURELET method. The consistent improvement in average SNR value of denoised images by 37.46 dB indicate that this algorithm is capable of handling varied degree of noise.

The high SNR is obtained due to negligible noise variance which represents that this method is capable of performing better denoising and simultaneously preserving edge information that corresponds to variations of thermal patterns. The SNR values of raw and denoised images of subjects with nodule are less scattered when compared to carcinoma and fibroadenoma cases. The SNR values of corresponding denoised images are increased by an average value of 41.34 dB.

Similar results are observed for benign tissues such as fibroadenoma and cyst. OWTSURELET algorithm is able to improve SNR value of denoised images of subjects with fibroadenoma and cyst by 37.16 and 42.65 dB respectively. The noise images have negligible edge details. This shows that OWTSURELET method is capable of eliminating noise effectively in all regions by preserving edge information corresponding to thermal variations.
Table 4.2 Statistical values of SNR of raw and OWTSURELET denoised normal and different pathological breast tissues

<table>
<thead>
<tr>
<th>Type of image</th>
<th>Mean ± Standard deviation of SNR(dB)</th>
<th>Raw</th>
<th>Denoised</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normal</td>
<td>33.23 ± 7.04</td>
<td>71.93 ± 0.98</td>
<td></td>
</tr>
<tr>
<td>Carcinoma</td>
<td>33.82 ± 7.21</td>
<td>71.28 ± 2.95</td>
<td></td>
</tr>
<tr>
<td>Nodule</td>
<td>30.98 ± 3.67</td>
<td>72.32 ± 0.66</td>
<td></td>
</tr>
<tr>
<td>Fibroadenoma</td>
<td>35.21 ± 8.78</td>
<td>72.37 ± 1.39</td>
<td></td>
</tr>
<tr>
<td>Cyst</td>
<td>29.63 ± 2.81</td>
<td>72.28 ± 0.84</td>
<td></td>
</tr>
</tbody>
</table>

The statistical values of SNR of raw and OWTSURELET denoised images for normal and different pathological breast tissues are presented in Table 4.2.

Figure 4.16 Comparison of estimated SNR values of BM3D and OWTSURELET denoising methods
The average SNR values of denoised images are twice that of raw images of normal and different pathological conditions. The standard deviation values of SNR of denoised images are low. The average SNR values of denoised images are relatively high for nodule and cyst conditions when compared to all other conditions. This shows that OWTSURELET could eliminate the noise effectively according to image properties.

Figure 4.17 Percentage change in estimated SNR values between raw and denoised images

Figure 4.16 shows the comparison of estimated SNR values for BM3D and OWTSURELET denoising methods. The standard deviation values of SNR seem to be high for BM3D when compared to OWTSURELET method. This may be due to blurring of edges during denoising process. The SNR values of OWTSURELET denoised images are high for all normal and various pathological conditions. This shows that the edge details in the final denoised image are improved by OWTSURELET method.
Figure 4.17 shows the percentage difference in the estimated SNR values between raw and denoised images. On average, 38% improvement in SNR value is observed for OWTSURELET denoising method. This emphasize that OWTSURELET shows better performance compared to BM3D denoising method. This could be due to adaptive multiscale product thresholding which makes this method optimal to sharp discontinuous in the image.

### Table 4.3 Statistical values of GMSD for BM3D and OWTSURELET denoised images

<table>
<thead>
<tr>
<th>Type of image</th>
<th>Average values of GMSD</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BM3D</td>
<td>OWTSURELET</td>
<td></td>
</tr>
<tr>
<td>Normal</td>
<td>0.0181</td>
<td>0.0054</td>
<td></td>
</tr>
<tr>
<td>Carcinoma</td>
<td>0.0193</td>
<td>0.0056</td>
<td></td>
</tr>
<tr>
<td>Nodule</td>
<td>0.0196</td>
<td>0.0063</td>
<td></td>
</tr>
<tr>
<td>Fibroadenoma</td>
<td>0.0188</td>
<td>0.0053</td>
<td></td>
</tr>
<tr>
<td>Cyst</td>
<td>0.0191</td>
<td>0.0061</td>
<td></td>
</tr>
</tbody>
</table>

Further, the edge preserving capability of denoising methods is compared using Gradient Magnitude Similarity Deviation (GMSD). The average values of GMSD for BM3D and OWTSURELET denoised images are tabulated in Table 4.3. The average values of GMSD of normal and pathological breast tissues are found to be low for OWTSURELET method when compared to BM3D. This shows that images’s local structures are not degraded and fine structural details are preserved. Hence, OWTSURELET method is found to be effective in performing noise removal and edge preservation. All these observations hold good when the edges are considered as the most important parameter for further processing of thermal images.
4.3 ANALYSIS OF RESULTS OF SEGMENTATION METHODS USING LEVEL SETS

The segmentation results generated using reaction diffusion and adaptive level sets on OWTSURELET based denoised images are presented and discussed.

4.3.1 Reaction Diffusion Level Set Method

The various stages of reaction diffusion level set segmentation for the representative OWTSURELET denoised image of a normal subject are shown in Figure 4.18. The initial contour of the level set function is defined on the image as shown in Figure 4.18 (b).

![Segmentation stages](image)

Figure 4.18 Representative segmentation of breast tissues using RDLSM: (a) Raw image (b) Initial contour (c) Gaussian edge map (d) Final evolved contour (e) Segmented mask and (f) Segmented image
The LSF evolves over several iterations according to the generated edge map shown in Figure 4.18 (c). The edge map generated represents the intensity gradient of the Gaussian filtered image and is used as stopping boundary for the level set function to settle in desired breast boundaries. At the end of 200\textsuperscript{th} iteration, a mask of final evolved level set contour is created. The final evolved level set contour and corresponding segmented mask are shown in Figures 4.18 (d) and (e). The segmented mask is multiplied with raw image in order to generate the final segmented breast region of interest and is shown in Figure 4.18 (f).

### 4.3.1.1 Choice of parameters

The optimal parameters of level set function are to be selected during evolution for precise segmentation. During the level set evolution, the parameter alpha provides additional force to drive the motion of the contour. For the images with weak edges, a large value of alpha causes boundary leakage. It is necessary to capture fine variations to detect the lower breast boundaries and infra mammary folds, and therefore a smaller value of alpha of 0.4 is preferred. The time steps for level set evolution (\(\Delta t\)) is set as 0.1. The dirac delta function helps to restrict the zero level set into a local neighborhood. The width of this function is defined by a positive constant \(\epsilon\). If it is too small, there are higher chances of the energy functional getting stuck at a local minima. On the contrary, for large value of \(\epsilon\), the final contour may not be accurate. Therefore, the parameter \(\epsilon\) is set to 1.5 throughout the experiment.

Gaussian edge map results in thick edges and leakage of contour is observed in lower breast boundaries as shown in Figure 4.18 (f). Hence, the level set performed either over or under segmentation leading to poor classification of breast thermograms of normal and abnormal subjects.
Figure 4.19 Representative segmented regions of interest using RDLSM for normal images: (a-d) Typical raw image (e-h) Gaussian, CED, TV and phase edge map and (i-l) Corresponding segmented image
Figure 4.20  Representative segmented regions of interest using RDLSM for abnormal images: (a-d) Typical raw image, (e-h) Gaussian, CED, TV and phase edge map and (i-l) corresponding segmented image.
The edge maps generated using different filters which include coherence diffusion, total variation and phase congruence are employed as stopping boundary for the segmentation of breast tissues. The raw image, edge maps obtained using Gaussian, CED, TV and PC filtering, and segmented breast tissues of normal and abnormal subjects are shown in Figures 4.19 and 4.20 respectively.

The optimum value of sigma of the Gaussian kernel is chosen as to be 0.8 according to the best visually smoothed image. The contrast parameter \( k \) in the diffusivity equation is chosen as 80 which results in high contrast edge map. Gaussian edge maps shown in Figures 4.19 and 4.20 (e) results in spurious edges which act as a hurdle for the free flow of LSF towards the edges and the boundary of the breast tissues results in thick edges. The movement of LSF is restricted due to false edge detail and the absence of clear edges near infra mammary folds. This shows that the level set contour is stuck to the false edge boundaries resulting in either over or under segmentation.

The breast tissues are lost near infra mammary folds due to the absence of clear edges in the segmented image of normal image and is shown in Figure 4.19 (i). Leakage of contour is observed in lower breast boundaries for the segmented image of abnormal subject as shown in Figure 4.20 (i).

The diffusion parameter sigma used in the edge stopping function of coherence enhancing diffusion filtering is fixed as 10. Time parameter, which decides the amount of diffusion, is fixed as 3. The pre and post smoothing parameter sigma gauss used for gradient calculation, is chosen as 1. The total diffusion process undergoes a maximum iteration of 100 to complete the filtering process. The edge maps extracted using coherence enhancing diffusion filtering for normal and abnormal images are shown in Figures 4.19 and 4.20 (f) respectively. These edge maps are found to be
brighter, distinct and more isolated from the nearby structures. This method is able to enhance the edges in different orientations and also avoids undesired blurring caused by conventional Gaussian filtering. However, the impact of steering diffusion in wrong directions may distort some genuine minutia points while creating fake ones.

The optimal values of process parameter chosen for the edge map extraction using TV based nonlinear diffusion filtering are time step of 0.2, the gradient regularization parameter \( \epsilon \) of 1 and the fidelity term \( \lambda \) of zero to maintain regular smoothing over different regions. The optimal parameters are chosen such that inner region is smoothened with lower gradient and the diffusion effect is stopped at the edges with higher gradient. The edge maps extracted using TV filter for normal and abnormal images preserve sharper boundaries, fine scale texture details of image and reduce undesired smoothing of the edges as shown in Figures 4.19 and 4.20 (g) respectively. These maps depict more localized edges in the mid infra mammary folds and lower breast regions. However, this method suffers from a well-known stair casing effects in regions with gradual image variations, blurring caused by conventional Gaussian filtering.

As thermal images lack in sharp boundaries, intensity gradient based edge detection algorithms fail to form distinct and meaningful boundaries as some parts of the contour leak through the weak boundary gradients, while some parts are confined inside the breast tissue. This boundary effect of weak edges is reduced with the use of gradient diffusion process and phase information in the segmentation process. Phase map is generated using log-Gabor filters. The parameters to be initialized in the filter design include the number of filter orientations, filter scales, filter bandwidth,
scaling between frequencies of successive filters, the minimum and maximum frequencies.

The prominence of the edge increases with number of orientations. For higher values, features other than edges also seem to become prominent. Therefore, with higher orientations, the initial contour gets stuck at the edge that is locally prominent and results in inaccurate segmentation. Hence, the optimal values of number of orientations are chosen as 4. It is observed that for lower number of scale, the lines and edges are not distinctly defined. For higher values of scale, features are over smoothed. After trading off the parameters, the number of scale is chosen as 4. The bandwidth is fixed at 0.55, resulting in a bandwidth of approximately 2 octaves. The scaling of 2.1 between center frequencies of successive filters resulted in the minimal overlap necessary to achieve fairly even spectral coverage of the entire bandwidth. The maximum frequency and minimum frequency are set as 0.33 and 0.035 by the wavelength of the smallest scale and largest scale filters respectively. The local phase is proposed as edge map. The edge maps for normal and abnormal images are shown in Figures 4.19 and 4.20 (h). The intensity and phase based edge maps are used as stopping boundary for the level set function to evolve towards the desired boundaries.

The local phase is not sensitive to the magnitude of boundaries in the image, hence phase map display the enhanced edge information that includes both the strong and weak edges. This allows segmentation along weak or strong boundaries between anatomical structures. The edges show the maximum PC and the initial contour evolves towards the breast boundary according to the strength of the edge information. The segmented breast tissues using phase map as edge information for normal and abnormal images are shown in Figures 4.19 and 4.20 (l).
The phase based method is able to identify and evolve perfectly near the lower breast boundaries and infra mammary folds using the obtained enhanced edge information. The thin edges are observed and thus, false boundary information and under segmentation are avoided. And also, most of the images are observed with continuous edges near lower breast boundaries and infra mammary folds. Even, in the case of subjects having small breasts with very weak boundary, the proposed segmentation algorithm results in accurate segmentation particularly near infra mammary folds.

### 4.3.2 Adaptive Level Set Method

The results of adaptive level set segmentation generated with different edge maps are presented. Figure 4.21 shows the various stages of segmentation algorithm. A representative raw image is shown in Figure 4.21 (a). The initial contour of the level set function is defined on the image as shown in Figure 4.21 (b). The initial contour of LSF is evolved according to the Gaussian edge map shown in Figure 4.21 (c). The blue line indicates initial contour whereas red line indicates final contour. At the end of the iteration, a mask of final evolved level set contour is created. The final evolved level set contour and corresponding segmented mask are shown in Figures 4.21 (d) and (e). The segmented mask is multiplied with raw image in order to generate the final segmented breast ROI and is shown in Figure 4.21 (f).

As thermograms lack in distinct edge information and definite shape, the parameters for level set method are chosen trading off the iteration number and convergence speed and are as follows: time step = 5, \( \mu = 0.04 \), \( \lambda = 5 \), \( k = 10 \) and \( \zeta = 15 \). The subjective analysis of the segmented output illustrates that the adaptive level set shows improved performance compared to RDLSM.
Figure 4.21 Representative segmentation of breast tissues using adaptive level set method: (a) Raw image (b) Initial contour (c) Gaussian edge map and (d) Final evolved contour (e) Segmented mask and (f) Segmented image

Boundary leakage near infra mammary folds and lower breast boundaries are found to be reduced due to nonlinear variation of adaptive velocity term. Gaussian edge map results in thick edges and leakage of contour is observed in lower breast boundaries. Hence, the level set performed either over or under segmentation. The edge maps generated using different filters which include coherence diffusion, total variation and phase congruence are employed as stopping boundary for the segmentation of breast tissues. The raw image, edge map obtained using Gaussian, CED, TV and PC filtering, and segmented breast tissues of normal and abnormal subjects are shown in Figures 4.22 and 4.23 respectively.

The edge maps of normal and abnormal images are extracted using coherence enhancing diffusion filtering are shown in Figures 4.22 and 4.23 (f) respectively.
Figure 4.22 Representative segmented regions of interest using ALSM for normal images: (a-d) Typical raw image, (e-h) Gaussian, CED, TV and phase edge map and (i-l) Corresponding segmented images
Figure 4.23 Representative segmented regions of interest using ALSM for abnormal images: (a-d) Typical raw image, (e-h) Gaussian, CED, TV and phase edge map and (i-l) Corresponding segmented images.
This edge map is able to enhance the edges in different orientations and also avoids undesired blurring caused by conventional Gaussian filtering. The edge map extracted using TV filter shown in Figures 4.22 and 4.23 (g) preserve sharper boundaries, texture and fine scale details of image and reduce undesired smoothing of the edges. These map depict more localized edges in the mid infra mammary folds and lower breast regions. However, this method suffers from a well-known stair casing effects in regions with gradual image variations.

As intensity gradient based edge detection algorithms fail to form distinct and meaningful boundaries, the phase information is embedded in the segmentation process. The phase based edge maps shown in Figures 4.22 and 4.23 (h) are able to drive the contour to evolve perfectly near the lower breast boundaries and infra mammary folds. Among various edge maps, phase based level set could extract breast tissues with distinct and clear boundary. The thin edges are observed and thus, false boundary information and under segmentation are avoided even near inframammary folds as observed in Figures 4.22 and 4.23 (l). Thus the algorithm could effectively move the contour towards the true edges and resulted in more accurate segmentation.

4.3.3 Validation of Segmentation Methods using Regional and Overlap Measures

The comparison of segmentation performance of RDLSM with various edge maps in terms of regional statistics and overlap measures are shown in Figures 4.24 and 4.25 (a) respectively. Significant improvement in the accuracy and specificity measures is observed for RDLSM with coherence edge map when compared to RDLSM with Gaussian edge map. Similarly, performance of the RDLSM with TV method is found to be much better than RDLSM with Gaussian and coherence methods. There is not much difference
Figure 4.24 Average variations of (a) Regional measures and (b) Overlap measures using RDLSM
Figure 4.25 Average variations of (a) Regional measures and (b) Overlap measures using ALSM
in terms of sensitivity as the proposed segmentation method faces challenges in the presence of discontinuous breast boundaries and results in over segmentation. Also, the variation in regional statistics measures among the considered image set seems to be consistent.

RDLSM with PC edge map could achieve significant improvement in terms of both regional statistics and overlap measures when compared to various other edge maps. Hence, this level set method is able to identify and evolve perfectly near the lower breast boundaries and infra mammary folds. DC measure shows that more than 94% of the segmented areas and GT areas are similar. Among all overlap measures, VS measure indicates maximum similarity 97% between segmented and GT images for this method.

The comparison of segmentation performance of ALSM with various edge maps in terms of regional statistics and overlap measures are shown in Figures 4.24 and 4.25 (b) respectively. The values of regional measures are found to be consistent for ALSM with different edge maps. Since the direction function and stopping force are adaptive in nature for different types of images, this segmentation method is able to identify the correct boundaries irrespective of the limitations of thermal images. ALSM with different edge maps could achieve high values of performance measures when compared to RDLSM with PC method.

Significant variation in the obtained measures of CED based ALSM method shows that the segmented results are not consistent across the image set considered. The thin edges of coherence filtered images result in more accuracy and specificity compared to Gaussian based ALSM. The performance of the TV based ALSM is found to be better than Gaussian and CED based ALSM methods, resulting in an average performance greater than 97%. Few segmented images are observed with infinitesimally breast tissue losses mainly near infra mammary folds, which is reflected in sensitivity and
specificity. Accuracy of 97% shows that this segmentation method is able to accurately extract the ROIs.

ALSM with PC method could achieve significant improvement in terms of both regional statistics and overlap measures when compared to all other edge maps. Significant improvement in the performance of the PC based ALSM method is observed with average performance greater than 98%. It is found that the trend of VS overlaps measure results with maximum of 99% similarity between segmented and GT images for this method. This shows that the proposed algorithm is able to extract the ROIs properly irrespective of limitations such as absence of clear edges and low contrast. Some of the segmented images are observed with breast tissue losses due to under segmentation. Further, the ALSM is able to identify and evolve perfectly near the lower breast boundaries and infra mammary folds using the obtained enhanced edge information.

The level set methods exhibit better performance in terms of regional and overlap measures for phase based edge map when compared to all other edge maps. Hence, the performance of segmentation methods with PC as edge map is compared and presented in Table 4.4. It is observed that ALSM method performs better than RDLSM with consistently high regional and overlap measures. This could be due to suppression of false boundaries by probability weighted stopping force. The amount of overlap region is relatively improved by 2% using ALSM method when compared to RDLSM due to the improved accuracy in the segmentation procedure. The phase based ALSM show slightly high improvement in all measures when compared to phase based RDLSM resulting in more accurate segmentation. The inherent limitations of thermal images are well handled by ALSM technique.
### Table 4.4  Average regional and overlap measure values of phase based segmentation methods for RDLSM and ALSM

<table>
<thead>
<tr>
<th>Measures</th>
<th>PC based segmentation method</th>
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<tbody>
<tr>
<td></td>
<td>RDLSM</td>
<td>ALSM</td>
<td></td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.97 ± 0.015</td>
<td>0.98 ± 0.005</td>
<td></td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.98 ± 0.028</td>
<td>0.99 ± 0.009</td>
<td></td>
</tr>
<tr>
<td>Specificity</td>
<td>0.96 ± 0.015</td>
<td>0.97 ± 0.010</td>
<td></td>
</tr>
<tr>
<td>PPR</td>
<td>0.95 ± 0.015</td>
<td>0.97 ± 0.011</td>
<td></td>
</tr>
<tr>
<td>NPR</td>
<td>0.99 ± 0.023</td>
<td>0.99 ± 0.008</td>
<td></td>
</tr>
<tr>
<td>JC</td>
<td>0.94 ± 0.030</td>
<td>0.96 ± 0.010</td>
<td></td>
</tr>
<tr>
<td>DC</td>
<td>0.97 ± 0.017</td>
<td>0.98 ± 0.005</td>
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</tr>
<tr>
<td>TM</td>
<td>0.94 ± 0.027</td>
<td>0.96 ± 0.009</td>
<td></td>
</tr>
<tr>
<td>VS</td>
<td>0.98 ± 0.012</td>
<td>0.99 ± 0.007</td>
<td></td>
</tr>
</tbody>
</table>

![Scatter plot between areas of ground truth and segmented images using PC based RDLSM](image)

**Figure 4.26**  Scatter plot between areas of ground truth and segmented images using PC based RDLSM
Figure 4.27 Scatter plot between areas of ground truth and segmented images using PC based ALSM

The areas of segmented breast tissues obtained using PC based RDLSM and PC based ALSM are correlated with that of GT images and as shown in Figures 4.26 and 4.27. A linear fit to these points show that the segmented areas and GT areas are highly correlated with R value of 0.98 for RDLSM and 0.99 for ALSM.

### 4.4 ANALYSIS OF RESULTS OF FEATURE EXTRACTION TECHNIQUES

The feature analysis of the segmented results generated using phase based ALSM segmentation method is presented and discussed. The changes induced by increased or decreased vascularity and angiogenesis due to different abnormal conditions namely, carcinoma, fibroadenoma, cyst and nodule are analyzed using transform based features.
Figure 4.28  Representative separated left and right regions of breast with different pathological conditions (a) Carcinoma, (b) Fibroadenoma, (c) Nodule and (d) Cyst

Prior to feature extraction, the left and right breast regions of segmented images are separated. Figure 4.28 shows the representative images of different pathological conditions considered and their corresponding delineated left and right breast regions.

Figure 4.28 (a) represents symmetrically separated left and right breast regions of a thermal image. The left breast region has malignant tissue and a region of increased vascularity can be seen as hot spot. Similarly, the thermal images with fibroadenoma and nodule in right breast regions are shown in Figure 4.28 (b) and Figure 4.28 (c) respectively. Figure 4.30 (d) shows the thermal image with cyst in left breast region.

The difficulty in understanding and differentiating these abnormalities can be easily seen from these images. The statistical texture features such as mean, kurtosis, skewness, coarseness, contrast and directionality derived from grouped healthy and pathological breast tissues
Figure 4.29  Average values of statistical features for (a) normal and abnormal breast tissues and (b) different abnormal breast tissues
are considered for analysis of breast tissues. The average values of these features are plotted in Figure 4.29.

The mean values of intensity variations of abnormal breast tissues are higher than that of normal tissues. This could be attributed to thermal variations induced due to abnormality. It is found that kurtosis values derived from normal breast tissues are low due to flat distribution of pixels. These values are high for abnormal breast tissues indicating the peakedness of probability distribution of gray levels.

Skewness values are found to be high in normal subjects. The boundaries of healthy breast tissues are clear and hence the contrast value is high for normal breast tissues. Also, these tissues possess high directionality when compare to abnormal tissues. This could be due to orientation of texture in a single direction.

Due to the presence of relatively large patterns of abnormalities, the values of coarseness are high and gray level distributions seem to vary widely for abnormal breast tissues. The values of contrast and directionality could provide distinct variations among different pathological conditions. This indicates that these features could capture variations of thermal patterns associated with pathological conditions.

Among all features, the values of kurtosis, skewness, contrast and directionality could differentiate normal and abnormal breast tissues. Hence these features are considered for analysis of breast pathological conditions.
4.4.1 Analysis of Wavelet Transform based Features

Transform domain representation of a breast thermal image capturing the underlying intensity variations is important in characterization of texture. The breast tissues are subjected to wavelet transform and various statistical texture features such as mean, kurtosis, skewness, coarseness, contrast and directionality are derived from approximation coefficients.

The normalized average values of statistical texture features extracted from the wavelet coefficients are shown in bar plot representation in Figure 4.30 (a). These features are able to differentiate the normal and abnormal breast tissues.

The average values of the texture features that could differentiate various pathological conditions are plotted in Figure 4.30 (b). The values of skewness and directionality are found to be high for fibroadenoma subjects. Among all features, the coarseness and directionality features could provide distinct differentiation among various pathological conditions.

4.4.2 Analysis of Radon Transform based Features

Radon transform allows representing edges and other singularities along lines in a more efficient way, in terms of compactness of the representation. The normalized average values of statistical texture features derived from Radon coefficients of the breast tissues are shown in bar plot representation in Figure 4.31. All the features except mean could differentiate normal and abnormal breast tissues. This may be due to thermal pattern variations leading to random gray level distributions in breast tissues.
Figure 4.30 Average values of wavelet based statistical features for (a) normal and abnormal, and (b) different abnormal breast tissues
Figure 4.31 Average values of Radon based statistical features for (a) normal and abnormal, and (b) different abnormal breast tissues
The kurtosis and skewness values show clear distinction between normal and abnormal breast tissues. This is due to asymmetric variations of thermal patterns caused by pathology occurring in these regions. It is observed that the mean values of coarseness are high for normal and abnormal breast tissues which may be due to the presence of relatively large variations of thermal patterns. Figures 4.31 (b) shows the variations of statistical texture features among abnormalities. The contrast and directionality features display distinct variation between healthy and abnormal tissues and are also effective in detecting pathological conditions present in breast tissues.

4.4.3 Analysis of Quaternion Hilbert Transform based features

The breast tissues are then subjected to QHT for extracting the frequency, amplitude, phase and direction components. The amplitude and phase components of QHT are obtained for normal and abnormal breast tissues are shown in Figures 4.32 (a-c) and (d-f) respectively.

![Figure 4.32](a) Normal breast tissue (b) corresponding amplitude and (c) phase components of QHT, (d) abnormal breast tissue (e) corresponding amplitude and (f) phase components of QHT

The statistical features derived from amplitude and phase images of QHT components of normal and abnormal breast tissues are shown in bar chart representation in Figures 4.33 (a) and (b). It is observed that the amplitude and phase features could differentiate normal and abnormal tissues.
Figure 4.33  Average values of QHT transform based statistical features for (a) amplitude and (b) phase components of breast tissues
Figure 4.34 Average values of QHT transform based statistical features for (a) amplitude and (b) phase components among abnormalities.
The differentiation of feature values between normal and abnormal tissues is high in phase component of QHT compared to amplitude. This indicates that the phase component of QHT could extract the thermal variations due to the pathological conditions. These features are able to capture the change in the vascular patterns in the breast regions more accurately.

The extracted features analyzed among the different abnormal conditions such as carcinoma, fibroadenoma, nodule and cyst are shown in Figures 4.34 (a) and (b). The features of amplitude and phase components of QHT are able to distinguish various pathological conditions. This indicates that QHT analysis could extract directional information of varied vascular patterns that are introduced due to increased metabolic activities.

4.4.4 Analysis of Riesz Hilbert transform based features

The breast tissues are subjected to Riesz Hilbert transform for extracting the frequency, amplitude, phase and direction components. The amplitude and phase components of Riesz transform obtained for normal and abnormal breast tissues are shown in Figures 4.35 (a-c) and (d-f) respectively.

Figure 4.35 (a) Normal breast tissue (b) corresponding amplitude and (c) phase components of Riesz transform, (d) abnormal breast tissue (e) corresponding amplitude and (f) phase components of Riesz transform
Figure 4.36  Average values of Riesz transform based statistical features for (a) amplitude and (b) phase of normal and abnormal breast tissues
Figure 4.37 Average values of Riesz transform based statistical features for (a) amplitude and (b) phase components of abnormal breast tissues
The values of statistical features extracted from amplitude and phase components of Riesz transform of normal and abnormal breast tissues are shown in Figure 4.36. The differentiation of feature values between normal and abnormal tissues is high in phase component. Among the six features, kurtosis and directionality derived from phase component could show the maximum variation between normal and abnormal conditions.

The extracted features are further analyzed among the different abnormal conditions and are shown in Figures 4.37 (a) and (b). These features are able to distinguish all pathological conditions significantly. It indicates the accurate extraction of varied vascular patterns that are introduced by increased metabolic activities.

4.4.4.1 Analysis of rotation invariant Riesz transform based features

The normal and abnormal breast regions are subjected to second order Riesz transform which allow analysis of thermal patterns on different scales and orientations. First and second scale representations of Riesz components for normal and abnormal breast tissues are shown in Figures 4.38 (a) and (d) respectively. The normal and abnormal breast tissues are subjected to second order Riesz transform with four Laplacian of Gaussian filters to extract the steerable property of thermal patterns.

The steerable basis function derives texture signatures from multiscale Riesz coefficients. Four scales of Riesz coefficients are obtained from the breast tissues. Statistical texture features such as mean, kurtosis, skewness, coarseness, contrast and directionality are extracted from the Riesz transform coefficients. Among four scales of Riesz coefficients, first two scales have good differentiation between normal and abnormal conditions compared to third and fourth scales.
Therefore, further analysis is based on first and second scales of Riesz coefficients. The values of statistical features derived from first and second scale outputs of Riesz coefficients of normal and abnormal breast tissues are shown in Figures 4.39 (a) and (b). The extracted statistical texture features are able to differentiate the normal and abnormal conditions significantly in both scales of Riesz coefficients.

The feature difference between normal and abnormal breast tissues is high for second scale Riesz coefficients compared to first scale. Dynamic ranges of gray levels are not uniform in healthy and pathological subjects. The high magnitude values of kurtosis for abnormal breast tissues indicate the peakedness of probability distribution of coefficients whereas the skewness values for normal breast tissues are high indicating the randomness of variations in structure caused by pathology affecting these regions. The boundaries of benign breast tissues are clear, while contrast value of malignant breast tissues is small due to the imprecise boundaries.
Figure 4.39  Average values of steerable Riesz transform based statistical features for (a) first and (b) second scale representation of normal and abnormal breast tissues
Figure 4.40 Average values of steerable Riesz transform based statistical features for (a) first and (b) second scale representation of different abnormal breast tissues
The normal images possess high directionality than the abnormal images. This could be due to orientation of texture of normal images in a single direction. Figure 4.40 (a) and (b) show the bar plot representation of extracted features of first and second scale output of Riesz coefficients for different abnormal conditions. It clearly demonstrates that second scale representation shows better localization characteristics of image due to steering of basis function in the direction of maximal response. The values of kurtosis, skewness, contrast and directionality obtained through statistical gray histogram distribution could effectively differentiate different abnormal conditions.

There is distinct variation in values of kurtosis between carcinoma and other benign pathological conditions. The variations in these values between fibroadenoma and nodule are less pronounced. The features contrast and directionality show distinct variations among pathological conditions.

4.4.5 Analysis of MQF based Features

The thermal images are subjected to MQF analysis to extract structural variations of thermal patterns.

![Figure 4.41](image)

(a) Normal breast tissue, corresponding global phase maps at (b) first and (c) second scales, (d) abnormal breast tissue, corresponding global phase maps at (e) first and (f) second scales
The local phase responses of the quadrature filter at different scales are integrated to generate the global phase map. The thermal variations are distinctly defined for second scale representation and hence considered for further analysis. The normal and abnormal breast tissues and their corresponding global phase maps at first and second scales are shown in Figure 4.41 respectively.

The statistical texture features such as mean, kurtosis, skewness, coarseness, contrast, and directionality extracted from the global phase map of the breast image are shown in bar plot representation in Figure 4.42. These features are able to differentiate the normal and abnormal conditions significantly.

There is distinct variation in values of kurtosis, skewness and contrast between normal and abnormal breast tissues. The average value of mean feature is high for abnormal breast tissues due to thermal variations induced by pathological conditions. Figure 4.43 shows the variations of statistical texture features among abnormalities.

The skewness, contrast and directionality features are significant in differentiating the abnormal breast tissues due to the presence of heterogeneous patterns. The high magnitude value of kurtosis feature for carcinoma breast tissues is due to peaked distribution of MQF coefficients indicating the high metabolic activity. This shows that MQF analysis at second scale representation is able to capture structural variations of thermal patterns which are introduced due to varied metabolic activities.

The significance of the extracted features are further analysed by calculating the percentage variations obtained between normal and abnormal tissues and are tabulated in Table 4.5.
Figure 4.42 Average values of MQF based statistical features for second scale representation of normal and abnormal breast tissues

Figure 4.43 Average values of MQF based statistical features for second scale representation of different abnormal breast tissues
Table 4.5 Percentage variations in feature values between normal and abnormal breast tissues for all transform techniques

<table>
<thead>
<tr>
<th>Transform Methods</th>
<th>Percentage Difference (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Kurtosis</td>
</tr>
<tr>
<td>Spatial image</td>
<td>3</td>
</tr>
<tr>
<td>Wavelet</td>
<td>4</td>
</tr>
<tr>
<td>Radon</td>
<td>4</td>
</tr>
<tr>
<td>Quaternion</td>
<td>6</td>
</tr>
<tr>
<td>Riesz</td>
<td>5</td>
</tr>
<tr>
<td>Steerable Riesz</td>
<td>10</td>
</tr>
<tr>
<td>MQF</td>
<td>23</td>
</tr>
</tbody>
</table>

Among the six features, kurtosis, skewness, contrast and directionality features from second scale Riesz and MQF coefficients have enhanced the difference value between normal and abnormal conditions by 10%, 9%, 13%, 9% and 23%, 23%, 28%, 10% respectively. Thus the results shows that, among all considered transforms, steerable Riesz transform and MQF analysis could efficiently exploit the local organizations of scales and directions of thermal patterns. It is evident that the extracted features could differentiate the normal and abnormal conditions significantly.