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ORIGINAL CONTRIBUTION

Morphological Enhancement of Microcalcifications in Digital Mammograms

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Abstract Mammography is a commonly used technique for early detection of breast cancer. In mammograms, microcalcifications show low contrast margin with the background parenchymal tissue (specifically when the background tissue type is fibroglandular) as a result, subjective analysis of these calcifications with respect to their size, shape and morphology presents a daunting challenge even for experienced radiologists. Thus the present work investigates the potential of two morphological techniques i.e., top-hat morphological processing and h-dome morphological processing for enhancement of microcalcifications embedded in variety of background tissue types including fatty, glandular and fibroglandular tissues while restoring their shape and size. The enhancement results are also compared with standard contrast limited adaptive histogram equalization method. For subjective analysis, 25 synthetic images with simulated microcalcifications of various shapes and sizes are used. Objective analysis is carried out on 50 mammographic images taken from benchmark dataset (McGill University mammographic database) by computing quantitative indices like contrast improvement ratio and detail variance/background variance ratios. After rigorous experimentation on both synthetic and benchmark data set it was observed that h-dome morphological processing (with $h = 60$) is ideally suited for enhancement of microcalcifications while restoring their shape and size.

Keywords Digital mammography · h-dome morphological processing · Top-hat morphological processing · CLAHE · Microcalcifications · Enhancement

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Introduction

Breast cancer is a common disease for women above 40 years of age [1]. Mass screening, periodic mammography and clinical examination leads to early detection which results in better disease management and reduces the death rate [1–3]. A cluster of microcalcifications in a mammogram may represent a benign or malignant condition. Experienced radiologists visualize the shape, area, other geometrical properties of individual calcifications in a cluster and also the density of microcalcifications in a cluster to arrive at the conclusion. Though experienced radiologists diagnose with good accuracy, still the possibilities of false detection remain considerable [4]. The main reason is that in mammograms, microcalcifications show low contrast margin with the surrounding tissue texture as a result certain microcalcifications having almost similar contrast with respect to the background may not be visible. The present work addresses this issue and recommends an enhancement method specifically tuned for enhancing the microcalcifications while restoring their shape and size.

Different approaches for enhancement of mammograms, including conventional image enhancement techniques such as histogram equalization, contrast stretching, unsharp masking, contrast limited adaptive histogram equalization (CLAHE) and various region based as well as feature based enhancement methods were reviewed in the article by Chang, et al [5]. Among these algorithms, it is reported that conventional methods are not suitable for enhancement of mammograms as they result in enhancement of microcalcifications as well as the background tissue texture. The study in the article by Papadopoulos, et al [6] reported the effect of five different enhancement algorithms, including CLAHE, enhancement by local range modification, enhancement by redundant discrete wavelet transform, enhancement by linear stretching and shrinkage algorithms on two different benchmark datasets and proposed that local range modification and wavelet based linear stretching are better suited for detection of microcalcification clusters. The enhancement approach experimented in study [7] first filters the mammographic image with a filter sensitive to contrast and shape of microcalcifications. The filtered image is then enhanced by wavelet based sharpening algorithm. Their subjective analysis carried out with the help of opinion from four radiologists indicates good enhancement and improved detection of clustered microcalcifications. The study in the article by Branimir, et al [8] proposed a computer aided visualization (CAV) system which can help radiologists in visualizing the clusters of microcalcifications in digital mammograms. Their design of CAV demonstrates use of mathematical morphology based approach for enhancement of microcalcifications and multifractal based approach for segmentation of microcalcifications with user selected threshold to control the level and quality of segmentation. Their experimentations demonstrate enhancement of local contrast with suppression of background tissue texture by addition of difference image obtained by subtraction of top-hat and bottom-hat images with the original image. The study in the article by Kimori, et al [9] demonstrated improved enhancement in medical images including mammograms with rotational morphological processing (RMP) in comparison to other conventional techniques by computing contrast improvement ratio. The study in the article by Singh, et al [10] designed a computer aided diagnostic (CAD) system for classification of microcalcifications in digital mammograms. Their study demonstrates increase in classification accuracy after preprocessing the mammograms by morphological enhancement approach based on computing the dual area top-hats in parallel. The study in the article by Khehra and Pharwaha [11] proposed a method of mammogram image enhancement by wavelet based hybrid approach in which approximation coefficients are altered by fuzzy transformation and detail coefficients are altered by non-linear transformation. Their reconstructed images with modified coefficients indicate good enhancement as validated objectively by values of information entropy and peak signal to noise ratio (PSNR).

From the studies reported in the literature for enhancement of microcalcifications in digital mammograms, it is observed that most of the work is on direct histogram modification methods, spatial domain methods, transform domain methods and mathematical morphology based enhancement methods. The advantage of mathematical morphology methods is enhancement of specific target features and suppression of the surrounding tissue texture which usually results in high local contrast and visualization of desired features embedded in dense background tissue. Thus in the present work the performance of two mathematical morphology based approaches i.e., top-hat morphological processing and h-dome morphological processing for enhancement of microcalcifications in mammograms is evaluated by subjective as well as objective analysis. The comparison of performance of morphological approaches with standard conventional CLAHE approach is also carried out.

The rest of this paper is organized as follows. "Materials and Methods" presents a brief description of image databases used and discusses the basic concepts underlying CLAHE, top-hat morphological processing and h-dome morphological processing. The evaluation indices used in this study i.e., contrast improvement index (CII) and detail variance to background variance ratio (DV/BV ratio) are also discussed. "Results and Discussion" illustrates the images that result by applying enhancement techniques to synthetic mammograms with simulated microcalcifications as well as on images obtained from McGill University database. "Conclusion" states the conclusions drawn.

Materials and Methods

Image Database

Synthetic Image Database

For subjective analysis, a synthetic image database of 25 images containing simulated microcalcifications of various shapes and sizes embedded on variety of background tissue types was created. The normal portions from the images contained in the benchmark McGill University mammographic image dataset were cropped and used as background for creating synthetic images. The horizontal as well as vertical resolution of these images is 144 dpi. The size of the simulated calcifications is < 3 mm. The synthetic image database was created for subjective analysis of performance of enhancement algorithms with respect to enhancement of microcalcifications while restoring their size and shape. The synthetic images were processed by CLAHE, top-hat morphological processing and h-dome morphological processing. The parameters associated with CLAHE i.e., clip limit, region size and number of bins, parameters associated with top-hat morphological processing i.e., type of structuring element (SE) and sizes and shapes of SE and parameters associated with h-dome morphological processing i.e., value

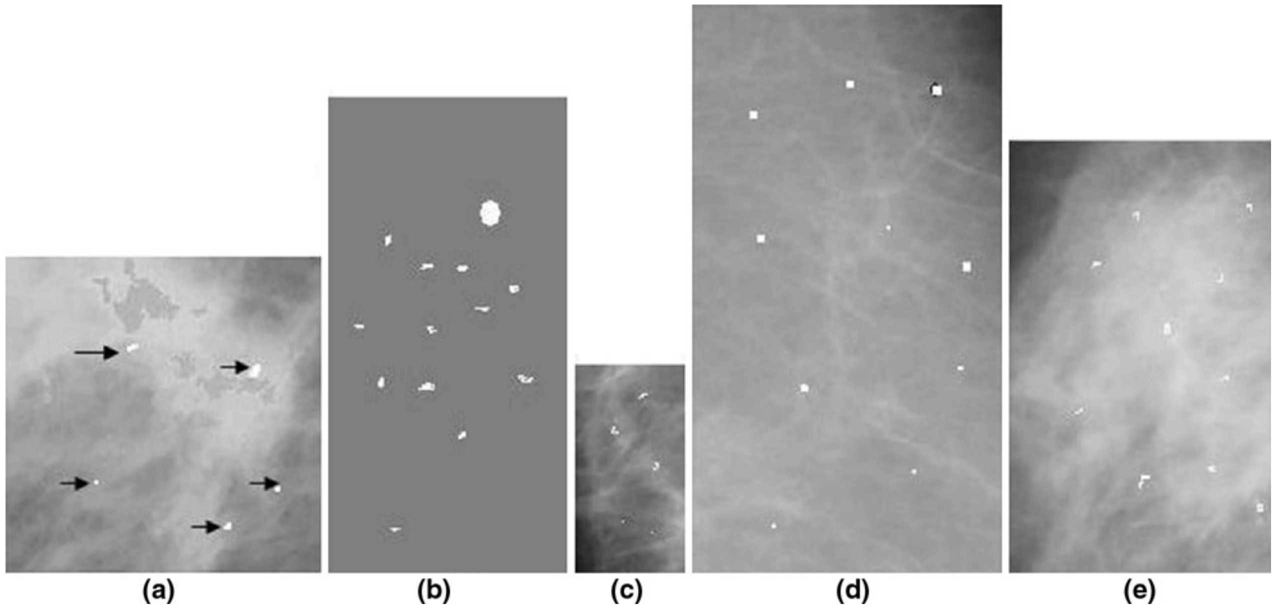

Fig. 1 Synthetic images with simulated microcalcifications of various shapes and sizes on background tissue with varying breast densities. On image **a** position of microcalcifications is indicated with arrows. Images **a**, **b**, **c**, **d**, and **e** contains 5, 13, 5, 10 and 10 microcalcifications, respectively

of h used to create the marker image were fine tuned by subjective analysis on the synthetic image database. Five synthetic images with simulated microcalcifications of various shapes and sizes selected randomly from the synthetic image database are shown in Fig. 1.

Benchmark Image Database

For objective analysis, 50 digital mammogram images obtained from McGill University database [12] were used to validate the performance of enhancement techniques. The horizontal and vertical resolution of these images is 144 dpi. The background tissues included in this database are of fatty, fatty glandular and dense glandular types. The regions of interest (ROIs) are extracted as per the information given in McGill University database. The enhancement techniques are applied to extracted ROI's. The objective assessment of CLAHE processing, top-hat morphological processing and h-dome morphological processing is carried out by computing quantitative indices i.e., CII and DV/BV ratio.

Enhancement of Mammograms

In case of mammographic images the preprocessing of original images is carried out in order to enhance the local contrast to sharpen the local features in the image which are important for clinical diagnosis. Selective enhancement can be achieved either by enhancing the ROIs or by removal of background tissue texture. The microcalcifications embedded in the dense mammographic tissue with non-uniform background can be easily visualized if enhancement and suppression of background tissue texture can be carried out simultaneously while restoring the sizes and shapes of microcalcifications.

Enhancement of Region of Interest

Contrast Limited Adaptive Histogram Equalization (CLAHE)

Contrast limited adaptive histogram equalization has been widely used for enhancement of medical images [13]. Instead of operating directly on the entire image, the CLAHE algorithm applies histogram equalization adaptively on small contextual data regions of the image [14]. The contrast of each contextual region is enhanced such that the histogram of each output region matches the specified histogram with uniform distribution. This evens out the distribution of gray level values used and makes the hidden features in the image more visible. The desired limit of contrast expansion (i.e., the maximum height of histogram of each output region) is controlled by user defined clip limit parameter [6]. The contrast enhancement is limited to avoid amplification of noise present in the image. The parameters of CLAHE algorithm are set as clip limit = 0.5, region size = 32 and number of bins = 256.

Enhancement by Removal of Background

In the present work, Mathematical morphological tools are used for processing the digital mammograms so as to suppress the background tissue texture thus increasing the

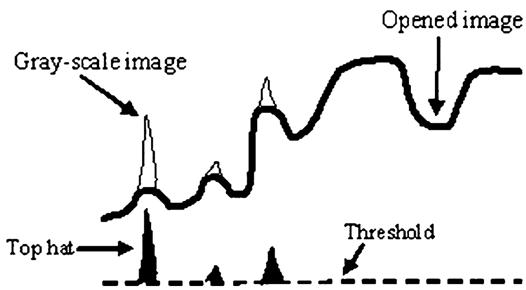

Fig. 2 Illustration of top-hat morphological processing on 1D profile of an image

gray level variations in image details. Any raw image I can be transformed into a new image Y by means of a morphological operator M on I with a user defined SE, such that, $Y = M(\mathrm{I;SE})$. All operations in mathematical morphology are based on two basic morphological operators i.e., dilation and erosion [8]. Opening and closing are two composite morphological operators constructed from basic dilation and erosion morphological operators. Opening is a result of erosion of image I with SE followed by dilation of eroded image with same SE, i.e., $Y = M_2(M_1(\mathrm{I;SE});\mathrm{SE})$, here, M_1 and M_2 represent erosion and dilation morphological operators, respectively. Opening removes bright spots i.e., peaks in intensities from the original image which are smaller than the SE.

Considering topographical representation of a digital mammogram each microcalcification can be assumed to represent a regional maximum. Regional maxima in any grayscale image I is represented as a set of connected components such that the gray level intensity of every pixel in the region is h and all pixels in the neighborhood have a lower gray level intensity value. To extract regional maxima (microcalcifications) embedded in digital mammograms two morphological techniques are used in this work. Top-hat morphological processing based on grayscale opening and h-dome morphological processing which based on grayscale reconstruction.

Top-hat Morphological Processing: Top-hat morphological processing uses gray scale opening to extract regional maxima or objects which differ in brightness from the surrounding background in images with uneven background intensity. The high intensity regions, i.e., the features that cannot accommodate the SE are removed by performing a structural opening. The features removed by opening are emphasized by subtraction of opened image (OI) from the original image (I), which yields a top-hat transformed image (THI) by using Eq. (1).

$$\mathrm{THI} = \mathrm{I} - \mathrm{OI} \text{ and } \mathrm{OI} = M_2(M_1(\mathrm{I};\mathrm{SE});\mathrm{SE}) \quad (1)$$

here, M_1 and M_2 represent erosion and dilation morphological operators. Top-hat morphological processing returns an image of objects from the input image which are brighter than their surroundings and smaller then the SE. The illustration of top-hat morphological processing on 1D profile of an image is depicted in Fig. 2 [15].

In top-hat morphological processing factors related to selection of appropriate SE such as type of SE, size and shape of SE affect the performance of enhancement [16]. In the present work, both flat SEs (square and disk shaped with various sizes) and non-flat SEs (ball shaped with various sizes) were experimented. After subjective analysis on synthetic image database, it was observed that with ball shaped non-flat SE (height = 50, radius =17), enhancement of microcalcifications is better in comparison with other SEs.

h-dome Morphological Processing: h-dome morphological processing is yet another algorithm used to extract

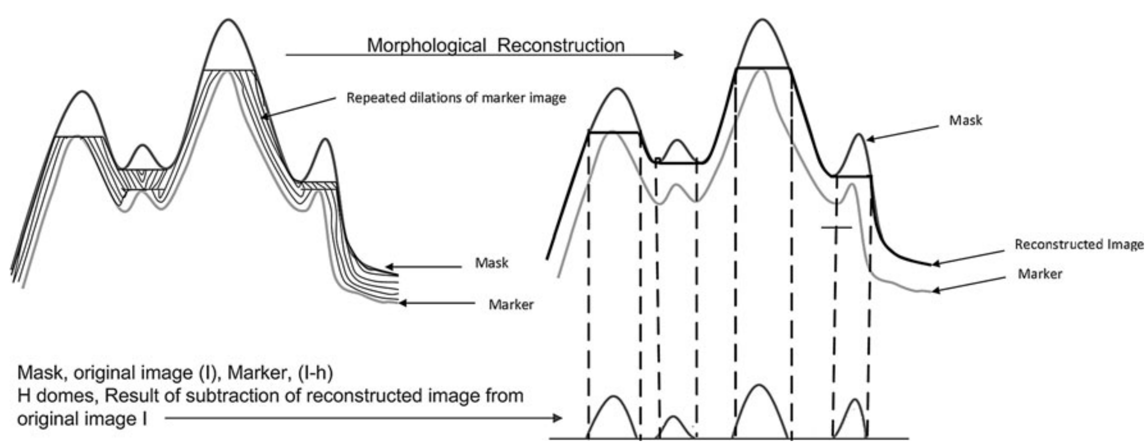

Fig. 3 Illustration of h-dome morphological processing on 1D profile of an image. *Note* Repeated dilations of marker image occur until it fits under the mask image. Peaks of the marker image spread out or dilate. Here, in morphological reconstruction, dilation is based on two images, mask image and marker image, instead of simple morphological dilation operation which uses one image and a SE. h-domes are extracted by subtracting the reconstructed image from the original image

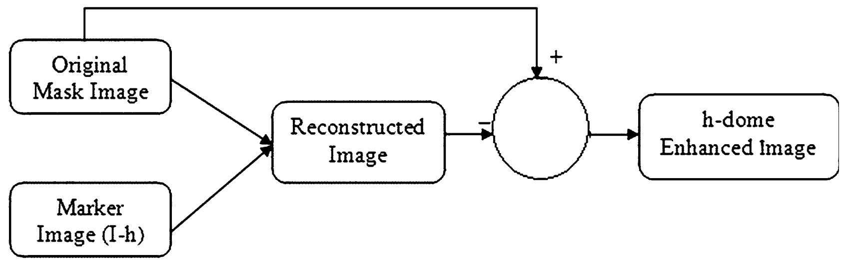

Fig. 4 h-dome morphological processing

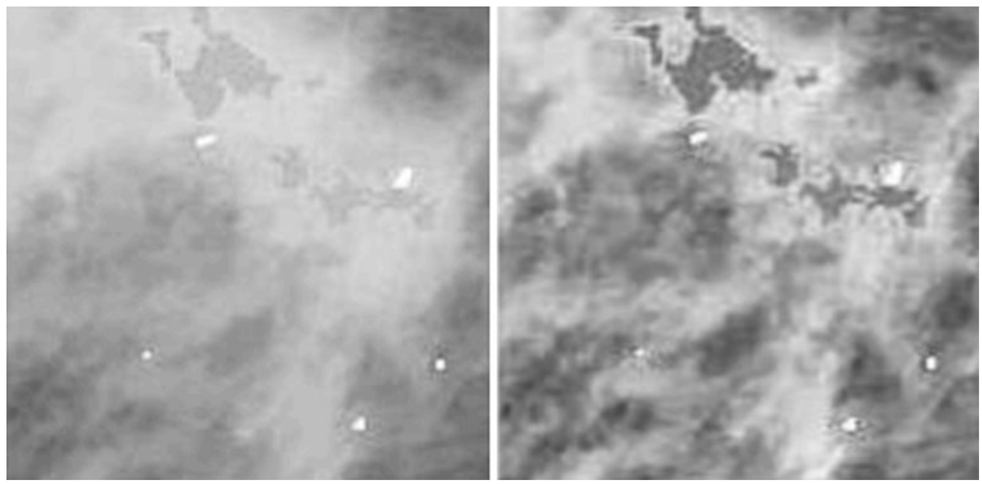

Fig. 5 Enhancement with CLAHE processing (clip limit = 0.5, region size = 32, number of bins = 256). *Note* CLAHE processing enhances simulated microcalcifications along with background noise

regional maxima based on grayscale reconstruction. Grayscale reconstruction is a morphological operator based on two images instead of a single image and a SE. In grayscale reconstruction the original image is the mask image and marker image is created by subtracting a constant value h from each pixel value in the mask image. The process of grayscale reconstruction can be viewed as repeated dilations of marker image under mask image. Each regional maxima of the marker image expands horizontally till it hits the mask image as visualized in profile of the reconstructed image in Fig. 3.

The final step of h-dome morphological processing is to subtract the reconstructed image from the original image as a result the processed image consists of domes of regional maxima from the original image [17]. The upper threshold on the sizes of all the extracted domes is user defined value h. The grayscale reconstruction ρ_{I} $(\mathrm{I}-\mathrm{h})$ of image I from marker image $(\mathrm{I}-\mathrm{h})$ is obtained by repeated dilations of $(\mathrm{I}-\mathrm{h})$ under I, until stability is reached [18], as given by Eq. (2).

$$\rho_{\mathrm{I}}(\mathrm{I}-\mathrm{h}) = \mathrm{V}_{n\geq 1}\partial_{\mathrm{I}}^{(n)}(\mathrm{I}-\mathrm{h}) \tag{2}$$

here, ‘V’ denotes point wise maximum operation, $\partial_{\mathrm{I}}^{(n)}$ represents n folds dilations on image $(\mathrm{I}-\mathrm{h})$. The dilations stopping point n is reached if the gray level intensity of any single pixel of dilated image $(\mathrm{I}-\mathrm{h})$ becomes equal to that of gray level intensity value of pixel in mask image I.

h-dome processed image h-dome (I) can be obtained by using Eq. (3).

$$\text{h-dome}(I) = \mathrm{I}-\rho_{\mathrm{I}}(\mathrm{I}-\mathrm{h}) \tag{3}$$

The illustration of h-dome morphological processing on 1D profile of an image is depicted in Fig. 3.

The block diagram of h-dome morphological processing is shown in Fig. 4.

In the present work, after rigorous experimentations based on objective evaluation on synthetic image database and subjective evaluation on benchmark database it was observed that h-dome processed mammographic images (with $h = 60$) enhance microcalcifications while preserving their size and shapes.

Quantitative Evaluation Measures

Contrast Improvement Index (CII)

The performance of image enhancement algorithm is often difficult to quantify. Theoretically, any enhanced image should allow better perception of desirable features in comparison to the original image. In the present work, quantitative measures like CII and DV/BV ratio are computed to validate the performance of enhancement algorithms.

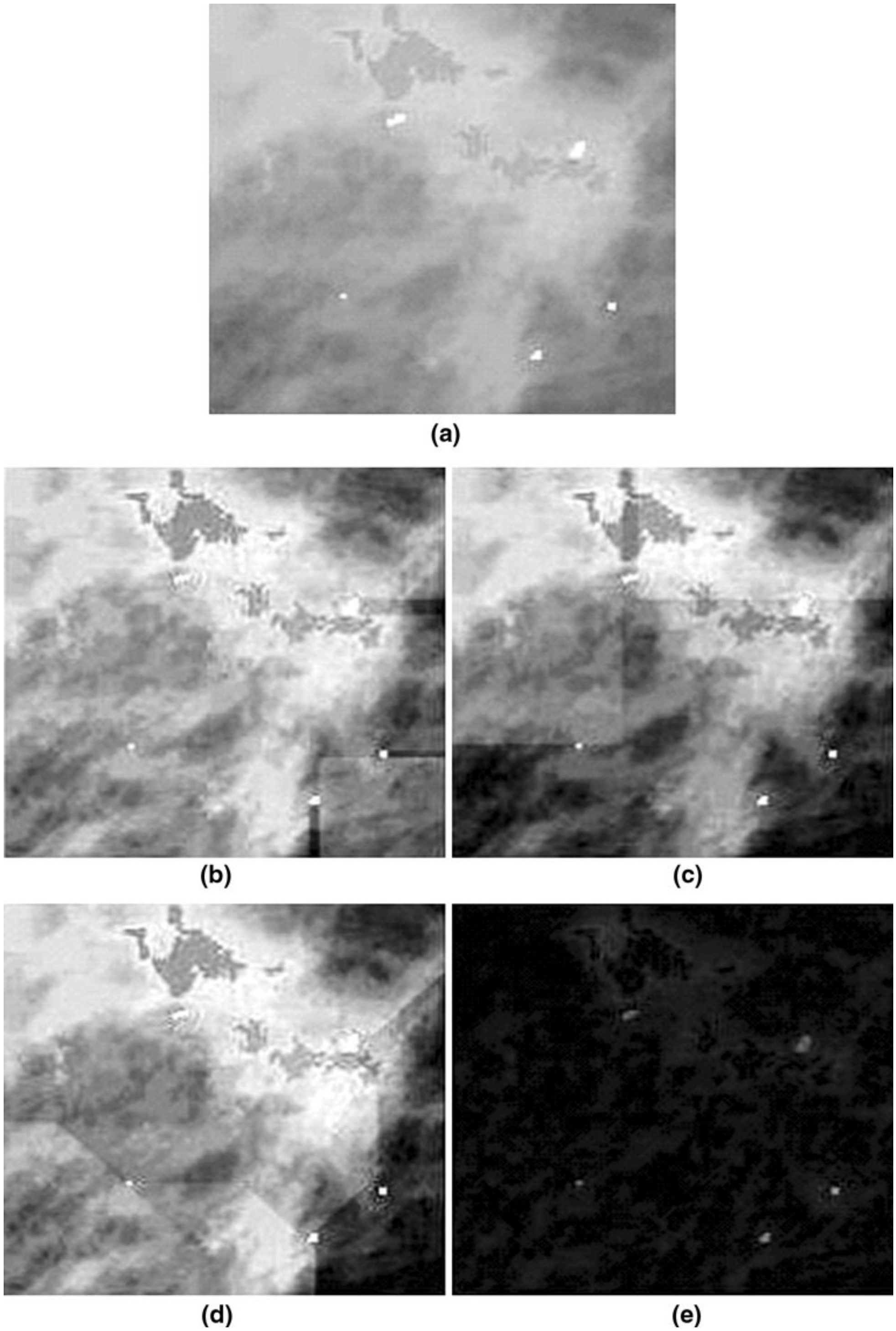

Fig. 6 **a** Synthetic image. **b** Enhanced with top-hat morphological processing with SE (square with side = 50). **c** Enhanced with top-hat morphological processing with SE (square with side = 100). **d** Enhanced with top-hat morphological processing with SE (disk with side = 50). **e** Enhanced with top-hat morphological with non-flat SE (ball with height = 50, radius = 17). *Note* Visually it can be observed that microcalcifications are perceived better in top-hat morphologically processed image with ball shaped non-flat SE (height = 50, radius = 17)

CII can be computed by using Eq. (4) [19].

$$\mathrm{CII} = \frac{C_{\mathrm{processed}}}{C_{\mathrm{original}}} \tag{4}$$

here, $C_{\mathrm{processed}}$ and C_{original} are the contrasts for region of interest in the processed and original images. The contrast C of a region is computed by using Eq. (5).

$$C = (f - b)/f + b \tag{5}$$

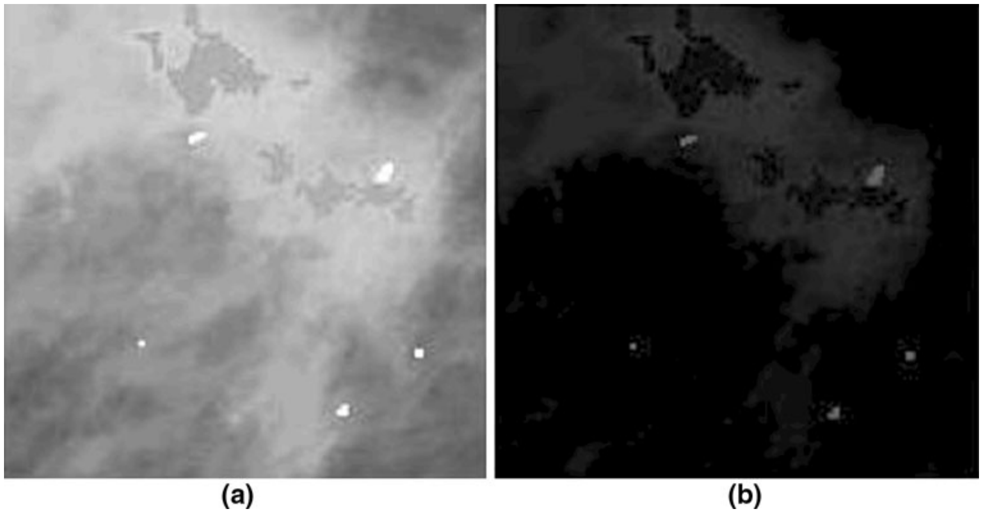

Fig. 7 **a** Synthetic image. **b** Enhanced with h-dome morphological processing ($h = 60$). *Note* Visually it can be observed that microcalcifications are perceived better in h-dome transformed image

here, f and b represent the mean gray-level intensity value of foreground and background, respectively. The higher the value of CII, the better is the performance.

Detail and Background Region Variance

The computation of DV/BV ratio (detail variance/background variance ratio) is based on calculation of detail variance and background variance. Detail variance is an estimate of the local variance in image details and background variance is the estimate of local variance in uniform areas. To compute detail variance and background variance each image pixel must be categorized as belonging to detail region or background region. For each pixel in the original image the variance in a [m × m] window is computed, if this value is greater than a fixed threshold, then the pixel belongs to the detail region; otherwise, it belongs to the background region. After categorizing each pixel in this manner, a binary map of the original image is obtained where, white pixels indicate detail region and black pixels indicate background region. Then, for each pixel of enhanced image the variance in a [m × m] is computed, if the corresponding pixel in the binary map of the original image is white, then this variance is added in a detail variance register, otherwise in a background variance register. After processing all the pixels in the enhanced image two numbers are easily computed, the average detail variance (DV), obtained by dividing the value in the detail variance register by the number of pixels in the detail region, and the average background variance (BV), obtained dividing the value in the background variance register by the number of pixels in the background region [20].

After enhancement it is expected that DV value should be larger than the one and BV value should not change or decrease slightly. The computation of DV/BV ratio depends upon two user defined parameters, the size of the window 'm' and the detail/background threshold. The higher the value of DV/BV ratio, the better is the performance.

Results and Discussion

Results for Synthetic Images (Subjective Evaluation)

Enhancement with CLAHE Algorithm

As shown in Fig. 5 it can be clearly seen that noise is also enhanced along with enhancement of microcalcifications and the structure of the background tissue is distorted.

Enhancement with Top-hat Morphological Processing

Enhancement of synthetic test image with five simulated microcalcifications using different structuring elements is shown in Fig. 6. It can be clearly seen from the images that for some structuring elements it shows better results as compared to others. For example, Fig. 6e enhanced by using ball shaped non-flat structuring element (height = 50, radius = 17) shows clear microcalcifications as compared to the other images. So it can be concluded that top-hat filtering depends on size and shape of structuring elements.

Enhancement with h-dome Morphological Processing

A synthetic image with five simulated microcalcifications enhanced by h-dome morphological processing is shown in Fig. 7. The h-dome morphological processing doesn't require any SE therefore tuning is only with respect to choice of threshold h which affects the performance of the

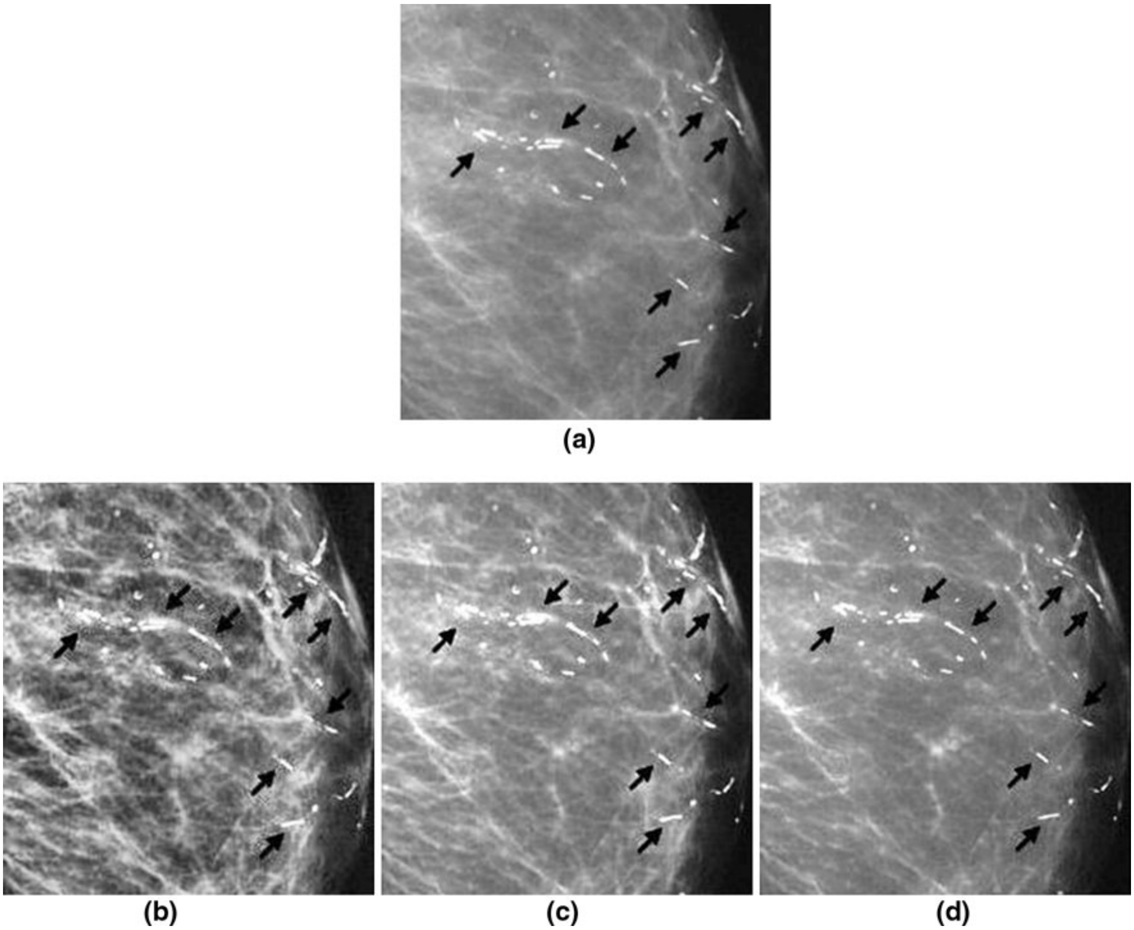

Fig. 8 **a** Original image (case 15Lmlo, cropped image-McGill University database). **b** CLAHE processed enhanced image (clip limit = 0.5, region size = 32 and no. of bins = 256) CII, 1.3765 DV/BV ratio, 1.3718. **c** Enhanced by top-hat morphological processing (non-flat SE, ball shaped, height = 50, radius = 17), CII, 1.8636, DV/BV ratio, 3.447. **d** Enhanced by h-dome morphological processing ($h = 60$), CII, 5.6711, DV/BV ratio, 6.0906. *Note* Visually it can be observed that enhancement of background noise is more in CLAHE processed images in comparison to top-hat and h-dome processed images. Top-hat processed images indicate good enhancement of microcalcifications but the shapes of some of the microcalcifications is changed. h-dome processed images enhance microcalcifications without affecting their shape and size

enhancement algorithm. After rigorous experimental testing it was found that for $h = 60$, the enhancement of microcalcifications with h-dome morphological processing is best.

It is observed that the acuity for microcalcifications is increased in h-dome processed image.

Results for Real Images—McGill University Database (Objective Evaluation)

Performance Evaluation with Quantitative Evaluation Measures

After getting confidence on synthetic images, all the three techniques discussed i.e., CLAHE, top-hat morphological processing and h-dome morphological processing were also applied on images obtained from McGill University database [12]. Enhancement for one of the images selected randomly is shown in Fig. 8. It can be clearly seen that h-dome processed image is better than the top-hat processed and CLAHE processed image.

Contrast Enhancement Index: The CII values were computed for 50 images from McGill University database. It was found that for 41 images CII is highest for h-dome processed images. The CII values for h-dome processed images varied from 0.0819 to 15.2404. The CII values for top-hat processed images varied from 0.1008 to 5.0706. The CII values for CLAHE processed images varied from 0.0547 to 5.9842.

DV/BV Ratio: The DV/BV ratios were computed for 50 images from McGill University database. It was found that for 33 images DV/BV ratio is highest for h-dome transformion. The DV/BV ratios for h-dome processed images

Table 1 Comparison of CII and DV/BV ratio values for CLAHE processed, top-hat processed and h-dome processed images for ROIs of mammograms containing microcalcifications obtained from McGill University database

	CII index values			DV/BV ratio		
IMAGES	**CLAHE**	**Top-hat**	**h-dome**	**CLAHE**	**Top-hat**	**h-dome**
1. case11Lcc_small_ans.jpg	0.493	1.2987	5.6131	1.8219	5.4592	7.3312
2. case11Lmlo_small_ans.jpg	2.7793	0.5437	1.9579	1.3823	3.4619	3.4094
3. case11Rcc_small_ans.jpg	0.1079	2.2725	8.7316	1.0263	5.4553	13.5619
4. case11_1Rmlo_small_ans.jpg	0.1241	3.2574	8.7838	1.1561	2.4988	3.0172
5. case15Lcc_small_ans.jpg	0.6527	1.2991	2.2072	1.4191	4.234	9.3933
6. case15Lmlo_small_ans.jpg	1.3765	1.8636	5.6711	1.3718	3.447	6.0906
7. case15Rcc_small_ans.jpg	0.481	4.5599	5.2196	1.1276	5.0099	8.5412
8. case15Rmlo_small_ans.jpg	0.6418	1.833	2.392	1.1266	2.8284	3.7901
9. case15_1Lcc_small_ans.jpg	0.2499	5.0706	4.918	1.0896	4.2247	6.9851
10. case15_1Lmlo_small_ans.jpg	0.6932	1.498	1.8621	1.2462	2.8486	6.0572
11. case15_1Rmlo_small_ans.jpg	0.0547	0.1008	6.2143	1.0904	3.9199	5.6203
12. case22Lcc_small.jpg	0.8216	0.9868	0.596	5.0901	15.8951	26.5558
13. case25Lcc_small_ans.jpg	1.2564	1.1051	5.9704	2.2488	7.032	5.7807
14. case25Lmlo_small_ans.jpg	2.2343	1.559	12.5288	1.8792	6.2937	5.0638
15. case25Rcc_small_ans.jpg	3.1077	0.8041	7.2974	2.2262	6.8286	3.7069
16. case37Lcc_ans_small.jpg	2.5223	1.5354	2.7563	1.6644	5.0736	4.8756
17. case37Lmlo_ans_small.jpg	0.9028	1.1311	2.4467	1.6825	6.2607	9.2017
18. case37Rcc_ans_small.jpg	1.9805	2.3513	15.2404	1.4907	3.8692	3.7868
19. case37Rmlo_ans_small.jpg	1.3164	1.3675	3.8337	2.2576	6.1862	8.2456
20. case46Lcc_small.jpg	0.4639	0.8848	2.8152	1.8267	5.2436	4.9238
21. case46Lmlo_small.jpg	0.7666	0.7883	3.5919	1.7104	5.4614	8.6311
22. case46Rcc_small.jpg	0.8822	1.0089	1.3031	2.4387	10.6359	24.573
23. case46Rmlo_small.jpg	0.4022	0.6451	3.2164	1.5705	4.381	6.7943
24. case49Lcc_small.jpg	0.9036	1.7152	6.4065	1.701	6.0728	8.571
25. case49Lmlo_small.jpg	2.1554	8.074	14.8162	2.1554	8.074	14.8162
26. case49Rcc_small.jpg	1.2976	0.8067	12.9275	2.1027	13.0858	46.8117
27. case49Rmlo_small.jpg	1.1905	2.3978	5.208	2.1847	8.8755	13.7816
28. case6Lcc_ans_small.jpg	0.2116	1.1966	3.3881	2.1628	6.0444	6.3396
29. case6Lmlo_ans_small.jpg	0.4271	1.1629	1.7586	1.6305	5.9265	7.5506
30. case7Lcc_small_ans.jpg	0.8138	1.1458	1.9992	2.4436	6.0634	4.639
31. case7Lmlo_small_ans.jpg	0.9706	1.1872	2.3027	2.0491	4.7484	4.9354
32. case7Rcc_small_ans.jpg	0.858	1.1433	0.4832	2.0525	4.4474	4.5907
33. case7Rmlo_small_ans.jpg	0.8328	1.1995	0.2002	1.8229	3.9807	2.6953
34. case17rmlo.jpg	0.5289	1.2171	0.5787	1.315	2.5792	2.9356
35. case19Rcc.jpg	5.9842	1.0575	2.2162	1.5545	4.9215	2.8494
36. case2.jpg	0.7273	1.1058	0.3297	1.9351	4.2781	7.3153
37. case21Lmlo.jpg	2.1772	1.5631	13.3021	1.3743	2.4113	4.3826
38. case24Lcc.jpg	1.1596	0.8069	8.3485	2.2081	12.1763	21.0072
39. case24Lmlo.jpg	0.8293	0.6032	5.3621	1.3668	3.6487	2.9172
40. case26Lcc.jpg	1.1631	0.7045	9.2249	1.8532	5.0935	4.0189
41. case27Rcc.jpg	0.6366	0.9595	0.975	1.7037	3.7338	3.9372
42. case27Rmlo.jpg	0.2922	0.8349	3.3956	1.5957	3.0757	2.9419
43. case2lmlo.jpg	0.7183	1.0391	0.0819	1.9093	3.7327	7.087
44. case36Lmlo.jpg	0.7396	1.2465	13.0567	1.845	4.0641	2.0411
45. case39Lcc.jpg	0.8749	1.07	1.0026	1.2838	3.4869	2.495
46. case39Lmlo.jpg	0.7471	1.314	0.9289	1.4351	2.9511	2.6567
47. case44Rcc.jpg	0.1877	0.9878	3.7911	1.9106	3.9924	3.7832
48. case44Rmlo.jpg	0.4768	1.1194	5.0349	1.6324	3.5514	4.2745
49. case5lcc.jpg	0.6757	0.8759	8.4431	1.6863	4.3485	6.3741
50. case5lmlo.jpg	0.8292	1.0102	1.0968	4.067	23.4492	44.4479

varied from 2.0411 to 46.8117. The DV/BV ratios for top-hat processed images varied from 2.4113 to 23.4492. The DV/BV ratios for CLAHE processed images varied from 1.0263 to 5.0901.

It has been observed that out of total 50 images of McGill University database, in case of 9 images for CII index and 17 images for DV/BV ratio the values are not highest for h-dome processed images. For visualization, these case mages are shaded with gray background in Table 1.

Higher values for CII and DV/BV ratio indicate better enhancement. From Table 1 it is can be seen that for most of the cases, h-dome processed images yields higher values for CII (i.e., for 41 out of 50 images) and DV/BV ratio (i.e., for 33 out of 50 images) in comparison to top-hat processed and CLAHE processed images.

Conclusion

The results of the experiments carried out on synthetic image database as well as benchmark image database indicate that h-dome processed images (with $h = 60$) are better suited for enhancement of microcalcifications while preserving their size and shape. The quality of top-hat morphologically processed mammograms for analysis of microcalcifications is dependent on proper selection of type, size and shape of the SE. It was observed that ball shaped non-flat SE (height = 50, radius = 17) results in better local contrast enhancement with suppression of the background texture in comparison to other SEs. Further the advantage with h-dome morphological processing is that it based on gray scale reconstruction unlike top-hat morphological processing which is based on grayscale opening which in turn requires selection of appropriate SE. It was observed that CLAHE processed images enhance microcalcifications as well as the background tissue. Thus it is difficult to analyse the shape and size of microcalcification in CLAHE processed images. The promising results of the study indicate that h-dome morphological processing is ideally suited for enhancement of microcalcifications in mammograms and can be routinely used to assist radiologists in clinical environment.

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