ISSN (Print) : 0974-6846
Indian Journal of Science and Technology, *Vol 8(22), DOI: 10.17485/ijst/2015/v8i22/79105, September 2015* ISSN (Online) : 0974-5645

A Survey on the Analysis of Segmentation Techniques in Mammogram Images

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Abstract

Background/Objectives: Images are the most effective way of revealinginformation to the world. Images are analysed and processed by computerized techniquesto extract hidden information available in it. Innumerable techniques are available to process the images. In numerous fields, the processed images are used for decision making. In medical field, automated detection and quantitative analysis of the radiological images and other images are processed by Computer Aided Diagnosis(CAD) tool to detect the abnormalities present in images. **Methods/Statistical Analysis:**Segmentation is one of the techniques used in CAD which play a vibrant role in processing the images. It is a process in which regions/ features sharing related characteristics are recognized or grouped together to interpret the images. Each segment divulges some information to the users. Segmentation techniques vary from image to image and areapplied to the images depending upon the problems being solved.This research work analyses about the segmentation techniques which are used in medical field. **Findings**: The results of the various research papers are discussed based on the approaches of hybrid algorithms applied in segmentation techniques. Also, this research work analyses about theuse of various segmentation techniques applied in mammogram images using CAD tool which assist the radiologist to interpret the suspicious regions and to know the impact of the diseases in patients for the suitable prediction. **Application/Improvements:** The segmentation techniquesare implemented to analyse mammogram images in future by means of a practical approach.

Keywords: Deformable Method, Hybrid Techniques, Image Segmentation, Mammogram Images

1. Introduction

The image is processed to retrieve the information without affecting the other features which is also present in the image. Processing of the images depends upon the application domain and approaches to solve it. The images are processed by using basic steps either to suppress the unwanted data such as noise or improve the quality of images for human visualization. Some of the application areas of image processing are medical field, remote sensing, pattern recognition, video processing and microscopic image and so on. Segmentation algorithms are based on two basic properties of intensity values; one is discontinuity and the other is similarity. Discontinuity is partitioning of an image based on abrupt changes in intensity. Similarity is partitioning of an image into regions based on similar set of predefined criteria[1]. Each segment of image reveals information in the form of colour, intensity or texture.

Recently segmentation techniques are implemented using Soft Computing, Hybrid techniques and Partial Differential Equation (PDE). Implementing segment algorithms using fuzzy, genetic algorithm and neural network falls under the soft computing approaches. Proposing segmentation algorithms by merging of two different techniques such as wavelet and neural network, wavelet and fuzzy, fuzzy and neural network, optimization technique and neural network are hybrid techniques. Developing segmentation algorithms by applying PDE is called as deformable model. Classical Active Contour

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(Snake), Gradient Vector Flow (GVF) and Geometric Active Contours are PDE methods.

Calcification is small calcium present in breast which is shown as a bright white spots. Tight clusters of calcifications known as microcalcification lead to a sign of breast cancer. It is of two types benign which is noncancerous and malignant which is cancer. Mammography is a premature diagnostic and screening tool to examine the breast cancer which uses low energy X-rays. In mammogram, the image appears in black, white and grey shades depending upon the density of the breast tissue. It appears white in colour when the tissue has high density. Fatty tissue appears in grey. It is very difficult to identify the abnormality present in dense tissue. Sensitivity and specificity are the two aspects to judge the eminence of mammogram. Sensitivity refers to how well the applied method identifies who has a disease. Specificity refers to how well applied method identifies who does not have a disease. Countless Computer Assisted Diagnosis (CAD) algorithms are developed to help radiologists to make decision regarding suspicious are asbut still it is a challenging task to the researchers. The different phases of image processing methods are shown in Figure 1. This research work analyses about the segmentation techniques which are used to classify medical images, particularly a deep review of mammogram images.

Organisation of the paper is as follows. Section 2 discusses about the use of segmentation techniques in image processing. Section III explores the segmentation methods implemented in medical images. Segmentation techniques applied in mammogram images by different researchers are discussed in section IV. Finally, Section V concludes the suitability of segmentation techniques in mammogram images.

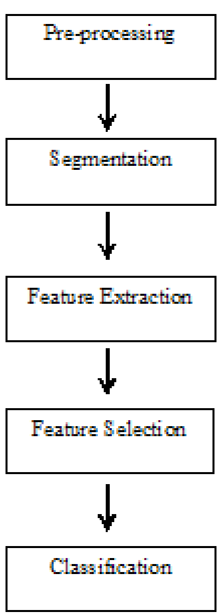


Figure 1. Phases of image processing.

2. Role of Segmentation in Image Processing

In recent years, extracting the facts from the image is a tough task in all the fields. In many areas, images are analysed for the improvisation of decision making. But, still it is difficult to make any precise decision from the obtained image. Some of the segmentation methods applied to different images is discussed in this section hereafter. Soma Banerjee et al. proposed an algorithm[2] to enhance and segment the SONAR image which is used to identify the obstacles present in the underwater. Lee filtering is used for denoising and adaptive dynamic stochastic resonance is applied in discrete wavelet to enhance Regions of Interest (ROI). Fuzzy C-Means (FCM) clustering is used to segment obstacle from ROI to calculate the size, position and centre of gravity. The performance of the proposed enhancement algorithm is measured using Peak Signal-to-Noise Ratio (PSNR) comparatively gives better result. The performance of the proposed segmentation algorithm is evaluated using Structural Similarity Index Measure (SSIM) which produced better result than adaptive thresholding based segmentation.

Vassilis Papavassiliou et al. developed two novel approaches to extract text lines and words from hand written document[3]. Piece-wise projection is used to segment gap and text from vertically divided image document. Veterbi algorithm is used to find the optimal succession of gap and text using the parameter obtained from HMM. The gap metric is used for word segment. The novel methods show better performance. Dina Khattab et al. proposed Grab Cut method which is modified using Orchard and Bouman clustering to eliminate user intervention at the early stage[4]. The method is also evaluated using RGB, CMY, YUV, HSV and XYZ colour spaces and in RGB colour space shows better segmentation. Ching Soon Tan et al. conferred a method to classify lobsters and burrows in underwater image[5]. In this work, median blur filter is applied to reduce noise and cropped the image to remove artifacts captured in the video. Optimum threshold value in a global window is calculated using Otsu's method and applied to image to segment region. The result showed the accuracy of lobster classification is 94.12% and burrow is 81.89%. Esmat Rashediand Hossein Nezamabadi-Pour proposed an unsupervised segmentation technique applied on colour image based on Gravitational Search Algorithm (GSA)[6]. The algorithm segment the image by region growing in feature space. The proposed method is evaluated by PSNR which showed better results than Statistical Region Merging (SRM) method. Figure 2 shows the colour image segmentation using SRM and GSA.

Rupali Telgad et al. applied histogram equalization to enhance and global thresholding to segment the finger print image[7]. In two iterations the algorithm showed the threshold value near a grey scale midpoint. Vipin V. discoursed about the forest fire detection using RGB and YC_bC_rcolourspace[8]. Sevenrules were defined to classify pixels as fire pixel. The proposed method achieves 99% flame detection rate. Two sets of images were used, one is fire in the image and other is fire like region.

3. Segmentation Techniques in Medical Images

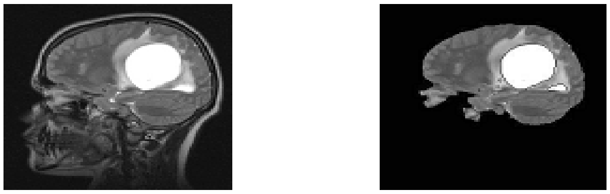
Radiologist analyse the images and interpret the abnormality present in it. CAD system helps the radiologist by improving the accuracy rate of the diagnosis. The output of the system and interpretation of radiologist will confirm the impact of the diseases. Some of the segment methods used in medical images is discussed in this section. Prabin and Veerappan[9] discussed a supervised contextual clustering with combination of region growing algorithm to segment lung CT image automatically. The proposed method is compared with traditional methods using 'Region props' function to evaluate accuracy and it produced better result. Radha and Bijee Lakshman confer a method to detect the exudates and to classify normal or abnormal retina[10]. Discrete Cosine Transforms (DCT) and morphology is used to enhance the ridges. The k-Means clustering algorithm is applied to detect exudates. Probabilistic Neural Network (PNN) is used to detect normal or abnormal retina. The method achieved an accuracy of 98%.

Alireza Osareh et al. discoursed about the segmentation of exudates using FCM[11]. In this work, it is done in two steps, in the first step coarse segment is done and in second step finer clustering is done. The method used for this research work attained 92% of sensitivity and 82% of specificity. Kalaiselvi Chinnathambi et al. applied k-Means, fuzzy k-means, moving k-means and adaptive fuzzy moving k-means method to segment the immature WBC from blood smear image[12]. In result discussion, it is concluded that adaptive fuzzy moving k-means is less sensitive to noise. Execution time is less than moving k-means and higher than k-means and fuzzy k-means. The performance of segmentation is high. Anas Quteishat et al. discussed a method to automatically classify cervical cells as normal or abnormal using fuzzy min-max neural network[13]. Fuzzy min-max neural network is used for classification. They achieved 75% of accuracy.

Weidong Zhang et al. proposed a novel vessel map-guided method to segment a small bowel in a Computed Tomography Angiography (CTA) image[14]. The small bowel is segmented using vessel map and fuzzy connectness technique. The method showed 82.5% of volume overlap accuracy. Thomas Walter et al. implemented an algorithm to detect optic disc using morphology operations and watershed transformation[15]. The observed outcome is compared with the result marked by the human specialist. The proposed method showed 92.8% of sensitivity. Qurat-ul-ainet al. proposed a method to diagnose brain tumourand classify the type of tumour[16]. Texture features are extracted from the input image and classification is performed using Ensemble Classifier. Malignant tumour is segmented using FCM. They achieved 99% of accuracy rate for classification of tumour. The original image and segmented tumour image are given in the Figure 3.

(a) (b) (c)

Figure 2. Colour image segmentation, **(a)** Original image, **(b)** Segmented using SRM and **(c)** Segmented using GSA.



(a) (b)

Figure 3. Medical image segmentation, **(a)** Original Image and **(b)** Tumour segmented image.

4. Analysing Mammogram Imagery

Various techniques are used to process the mammogram to reveal the data present in it. At the initial stage pre-processing of mammogram image is done in which pectoral muscle and breast regions are removed. Then suspicious regions are detected and based on some features which is extracted from the segmented region is used to classify the breast cancer as normal, benign and malignant. This section discusses about the different segmentation algorithms applied to mammogram images.

Danilo Cesar Pereira et al. developed a computational method to segment breast cancer in mammogramimage taken in Cranio Caudal (CC) and Medio Lateral Oblique (MLO)view[17]. They applied multiple threshold, wavelet transform and genetic algorithm to implement segmentation. The result produced 95% of sensitivity. Shanmugavadivu P and Sivakumar V discussed about the detection of Micro Calcification (MC) cluster based on sobel edge detection method in which fudge factor is replaced with Hurst Co-efficient[18]. Hurst Co-efficient is computed as the difference of fractal dimension and the topological dimension of input image. The proposed method produced better result. Aioub Zeinvand Lorestani et al. applied adaptive neuro-fuzzy system to segment the mammogram image[19]. Threshold limit is considered as 190. Pixels having more than 190 are considered as candidate pixel. The proposed method produced 95% of sensitivity and 98% of specificity. Sivakumar R et al. applied Fuzzy C-Means to segment the image[20]. Thresholding method is used to identify boundary of the breast. Pectoral muscle is determined and removed using modified tracking algorithm. Mentioned Selection of centre points randomly leads to optimal solution in FCM and suggested it can be solved by using Evolutionary algorithm.

Sheng zhou Xu et al. used watershed transformation to obtain the lesion boundary of smoothed morphological gradient image[21]. The proposed method is compared with dynamic programming boundary tracing method and the plane fitting and dynamic programming which produced better performance. Dheeba J and Tamil Selvi discussed about the detection of microcalcification using hybrid of Particle Swarm Optimization (PSO) and FCM[22]. The result produced 88.5% of detection rate. Ying-Che Kuo et al. discussed about the application of PSO to identify the masses[23]. Wavelet transformation is applied to enhancement the input image at the initial stage. 94.99% of detection rate is produced by the method. Mini MG, et al. applied multiplexed wavelet transform i.e. zero-crossings (M-Hdetector) and local extrema (Canny detector)of the wavelet coefficients at different decomposition levels[24]. 95% of sensitivity is produced by both the detectors. Alain Tiedeu et al. developed a method to detect microcalcification based on texture[25]. Input image is smoothed and subtracted from the contrast enhanced image of the input image. The detection method showed 85.65% of success rate with 2.50 FP image. The classifier showed better classification under ROC with 96.8%. Ted C. Wang and Nicolaos B. Karayiannis implemented wavelet based decomposition as a tool for segmentation. Mammogram is decomposed into different frequency subband[26]. The low frequency subband is supressed. Mammogram with high frequency is reconstructed which showed the presence of MC. The conclusion is to show the ability of the wavelet in mammogram image to detect MC.

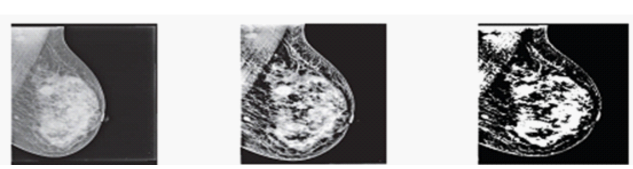
Dheeba J et al. proposed Particle Swarm Optimized Wavelet Neural Network (PSOWNN) method to classify normal and abnormal breast tissues[27]. PSOWNN classifier showed 94.167% of sensitivity, 92.105% specificity and 93.671% of accuracy than SONN and DEOWNN. Chun-Chu Jen and Shyr-Shen Yu developed automatic detection classifier which used to classify the abnormal tissues in mammogram[28]. Global equalization transformation, image demonising, binarization, breast object extraction, breast orientation determination and pectoral muscle suppression were carried out in pre-processing. The proposed method showed 86% of sensitivity with the textural features intensity and gradient. The ADC classifier also showed better performance. Xiaoyong Zhang et al. combined morphological operation and wavelet transform to detect MC[29]. The proposed method detected 92.9% of true MC cluster per image and 0.08% false MC cluster per image. Peyman Rahmati et al. presented a novel Maximum Likelihood Active Contour Model using Level Sets (MLACMLS)[30]. Segmentation contour is estimated using gamma distribution. Proposed algorithm is compared with Adaptive Level Set-Based Segmentation Method (ALSSM) and Speculation Segmentation using Level Sets (SSLS). The accuracy of MLACMLS is 86.85% whereas ALSSM is 74.32% and SSLS is 57.11%. The results are qualitatively compared with active contour and showed better performance.

Rahimeh Rouhi et al. developed two methods to segment the masses from the input image. In the first method automated region growing is used to segment in which threshold is obtained by Artificial Neural Network

(ANN)[31]. In the second method, the Cellular Neural Network (CNN) is used to segmentation in which parameters are obtained by a Genetic Algorithm (GA). The proposed method is compared with random forest, naïve Bayes, SVM, and KNN classifiers. The developed method obtained sensitivity 96.87%, specificity 95.94%, and accuracy 96.47%. Shradhananda Beura et al. implemented a method to classify breast tissues as normal, benign or malignant using wavelet and Grey-Level-Co-Occurrence Matrix (GLCM)[32]. The performance was compared with respect to accuracy and AUC of ROC. For normal and abnormal 98.0% of accuracy and for benign and malignant 94.2% of accuracy has been obtained in Mammographic Image Analysis Society (MIAS) database. In Digital Database for Screening Mammography (DDSM) database for the same parameters 98.8% and 97.4% were obtained.

Subodh Srivastava et al. implemented a combined approach for enhancement and segmentation using modified FCM in wavelet[33]. Proposed unsharp masking and sharpening method based on nonlinear complex diffusion. Proposed enhancement method is evaluated using Signal-To-Noise Ratio (SNR). Proposed segmentation is evaluated in terms of Random Index (RI), Variation Of Information (VOI) and Global Consistency Error (GCE). The evaluated result shows that execution time of segmentation method is less than the other method used for comparison. The segmented mammogram image using modified FCM is shown in Figure 4. Monica Jenefer and Cyrilraj proposed iterative modified watershed algorithm to segment the input image[34]. Speckle Noise Removal and EM algorithm is used for enhancing the image. GLCM is used for feature extraction. Classification is done using SVM. Performance metrics showed Sensitivity is 97.5%, Specificity is 100% and accuracy is 98%.

Arnau Oliver et al. analysed the mammogram image taken in different views[35]. The images of two different databases are taken and seven mass detection methods are compared. The review is performed on detection of mass



(a) (b) (c)

Figure 4. Mammogram image segmentation, **(a)** Original image, **(b)** Proposed nonlinear complex diffusion unsharp masking and sharpening and **(c)** Segmented image using modified FCM.

in single view-region based, contour based, clustering based and model based. They determined that Integrating Ipsilateral, bilateral and temporal mammogram detection results showed better improvement. Ramani R et al. reviewed various recent enhancement and segmentation techniques applied in mammogram image for the segmentation of the MC[36]. Shanmugavadivu P et al. proposed a novel segmentation method based on wavelet. Median filter is used for denoising the input image[37]. The result showed the abnormal region exactly. Shaji B et al. discussed the efficiency of BPNN and Radial Basis Function (RBF) in identifying MC present in mammogram[38, 39]. Input image is decomposed using wavelet. The statistical features are extracted from wavelet coefficients and is trained and tested with BPNN and RBF. The presence of MC is identified by RBF with one iteration whereas BPNN takes more iteration. Saleem Durai et al. proposed intensity based method to identify the mammogram is normal or abnormal[40]. The suspicious area is determined by threshold value greater than 140 and area has more than 100 pixels. The proposed method produced accuracy 91.66%, sensitivity 95% and specificity 85%.

Dubey RB, et al. proposed segmentation of masses using level set a method[41]. They use Gaussian filter for smoothing and noise reduction. The results are analysed visually by expert radiologist. Venkat Narayana Rao T and A. Govardhan proposed Fuzzy Enhanced Mammogram Segmentation (FEMS) in which two sub methods FEM1 and FEM2 are developed[42]. The performances of the two methods are evaluated using Similarity Index, Correct Detection Ratio and Under Segmentation Error. FEM1 performs well than FEM2. CDR for FEM1 is 87% while FEM2 gives 77% and consumes 6.25 times lesser processing time.

The Table 1 shows that the summary of various methods proposed by different researchers in segmenting and classifying the tumour. Most of the proposed methods are integration of different techniques. Mammogram images mainly undergo three stages of processing: 1. Pre-processing; 2. Segmentation; 3. Classification. Pre-processing is done to remove superfluous data. Segmentation is done to extract the anomalous regions. Classification is done to identify the cancer type. Texture, shape, size and intensity of masses or microcalcification are used as features. The feature selection algorithms are used to extract the required features. Based on the extracted features the classification as benign or malignant is performed using classifier. The accuracy, sensitivity

Table 1. Results comparison

Paper Ref. No.	Author Name	Proposed Method	Results		
			Accuracy	Specificity	Sensitivity
[17]	Danilo Cesar Pereira et al.	Wavelet transform and GA	--	--	95%
[19]	Aioub Zeinv and Lorestani et al.	Neuro-fuzzy	--	98%	95.00 %
[22]	Dheeba J and Tamil Selvi	PSO and FCM	--	--	88.50 %
[23]	Ying-Che Kuo et al.	PSO Wavelet transformation	--	--	94.99 %
[24]	M.G. Mini et al.	Multiplexed wavelet transform	--	--	95.00 %
[25]	Alain Tiedeu et al.	Textural features,ANN	--	--	85.65 %
[27]	Dheeba J et al	PSOWNN	93.67%	92.105%	94.17 %
[28]	Chun-Chu Jen and Shyr-Shen Yu.	Textural features PCA	--	--	86%
[29]	Xiaoyong Zhang et al.	Morphological operation and wavelet transform	--	--	92.9% per image
[30]	Peyman Rahmati et al.	Maximum likelihood active contour model using level set	86.85%	--	--
[31]	Rahimeh Rouhi et al.	CNN and GA	96.47%.	95.94%,	96.87%,
[32]	Shradhananda Beura et al.	Wavelet and GLCM	MIAS 94.2% , 98.0% DDMS 98.8% 97.4%	--	--
[34]	Monica Jenefer and Cyrilraj	Proposed iterative modified watershed algorithm	98%	100%	97.5%,
[40]	Saleem Durai et al.	Intensity and FCM based segmentation	91.66%	85%.	95%
[41].	Dubey R. B	Level set a method	The results are analysed visually by radiologist		
[42].	Venkat Narayana Rao T and A. Govardhan	Fuzzy Enhanced Mammogram Segmentation (FEMS)	FEM1 outperforms than FEM2 and processing time is less		
[38,39]	Shaji B et al.	Wavelet and BPN, Wavelet and RBF	RBF identified MC in one iteration		
[35]	Arnau Oliver et al.	Compared quantitative of detection method taken in different views	Integrating Ipsilateral, bilateral and temporal mammogram detection results showed better improvement		
[33]	Subodh Srivastava et al.	Modified fuzzy in wavelet domain	Execution time of segment algorithm is less		
[18]	Shanmugavadivu P and Sivakumar V	Fractal based detection	Produced better result		
[37]	P. Shanmugavadivu et al.	Wavelet based segmentation	abnormal region are extracted exactly		
[26]	Ted C. Wang and Nicolaos B. Karayiannis	Segmentation using wavelet	Showed the ability of wavelet in MC detection		
[20]	Sivakumar R et al.	Modified tracking algorithm and FCM	Selection of centre points randomly leads to optimal solution in FCM		

and specificity are computed to show the performance of the applied techniques. The performance of proposed methods are also evaluated using different metrics such as ROC curve, FROC curve, Area Overlap Metric (AOM), RI, VOI and GCE.

5. Conclusion

The novelty of automatic diagnosis in mammogram images requires progress and modernization. Various methods were developed to segment the mammogram images and assist the radiologists to make a decision. But, still no unique method was developed to segment the entire suspicious regions in mammogram. This research work analysed the different methods proposed by various researchers in segmenting the mammogram imagery. Each category shows its performance vibrantly. From this survey oriented research work, it is identified that most of the hybrid techniques yields good accuracy, sensitivity and specificity in order to segment and classify the mammogram images. Hence, any hybrid technique performs well in segmenting the mammogram images compared with existing methods.

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