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Research paper

Effective Texture Features for Segmented Mammogram Images

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Abstract

Textures of mammogram images are useful for finding masses or cancer cases in mammography, which has been used by radiologist. Textures are greatly succeed for segmented images rather than normal images. It is necessary to perform segmentation for exclusive specification of cancer and non-cancer regions separately. Region of interest (ROI) in most commonly used technique for mammogram segmentation. Limitation of this method is that it unable to explore segmentation for large collection of mammogram images. Therefore, this paper is proposed multi-ROI segmentation for addressing the above limitation. It supports greatly for finding best texture features of mammogram images. Experimental study demonstrates the effectiveness of proposed work using benchmarked images.

Keywords: *ROI, Mammogram segmentation, multi ROI segmentation.*

1. Introduction

Image segmentation is an important task in mammography that useful for extraction of effective textures for the mammogram images. Segmentation provides required cues regarding to textures [9] of cancer and non-cancer regions in mammograms. Textures are different shapes or distinguishable patterns and it may require distinguishing the textures between cancer and non-cancer cases for mammogram images based on detection of irregularities. Segmentation based textures is composed of two key steps, these are, segmentation of mammogram image and extraction of texture features for specified regions of mammogram images. Region of interest (ROI) is effectively support to segmentation that helps to identification of suspected masses.

Segmentation is a one of key problem that used to distinguish the masses or relevant objects from background. Mammogram segmentation is used toextract the edges or boundaries of respective images. In mammogram images, it is important to distinguish the suspicious cancer region and its surroundings. Usually a high intensity and circular based objects are more likely to be ill-defined masses [11]. Texture is one of the visual features playing an important role in scene analysis. Intuitively, it is related to patterned variations of intensity across an image. Texture segmentation [13] in general is composed of two steps, namely, the extraction of texture based features and secondly the grouping of these features.

ROI segmentation is effectively performs the segmentation of various regions in mammogram images. In mammogram classification, we have taken a large number of mammogram images for training or building models of cancer and non-cancer images. However, ROI [2] is unable to support segmentation for large number of mammogram images. For this reason, this paper proposed multi-ROI technique for addressing this problem.

Multi-ROI based textual features are more attractive than norm ROI based textual features. In this paper, we analyzed several important textual features for both ROI and multi-ROI techniques. These textual features are as follows: mean, standard deviation, entropy, variance, smoothness, kurtosis, skewness, contrast, correlation, energy, homogeneity. Texture analysis is popular concept and it is widely used inimage processing for segmentation and classification mammogram images is based on a local gray level variation of intensity of pixels. The statistical approach describes the various texture properties that are suitable if texture primitive sizes are comparable with the pixel sizes. Statistical approaches may describe the texture by the non-deterministic features or properties that consists relationships between the gray levels of an mammogram images.

Contributions of this paper are summarized as follows:

1. Segmentation is performed for mammogram images using existing ROI and proposed multi-ROI for large collection of mammogram images
2. Texture features are derived for segmented images
3. Analyze the texture features for abnormality cases of pre-processed mammogram images
4. Comparative study is performed between normal ROI segmentation and multi-ROI mammogram segmentation

Remaining sections of this paper is organized as follows: Section 2 presents the background study, Section 3 presents the proposed multi-ROI segmentation, Section 4 presents the results discussion and Section 5 presents the conclusion of the work.

2. Background Study

The artifacts and noise suppression mechanisms are frequently used in pre-processing of mammogram images; mammogram image segmentation [7]is useful for identifying of tumor or any suspicious areas during mammography and these suspicious regions are specifically called as region of interests (ROIs) [2]. Purpose of ROI segmentation is to determine the region of

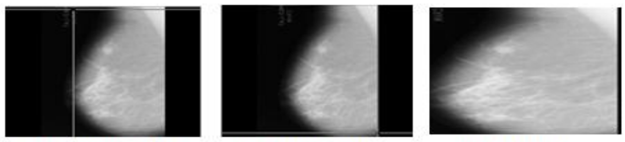
interests on suspected areas of mammogram that indicate breast abnormalities [12] includes either tissues or masses in mammogram. ROI segmentation is used for finding suspicious lesions in mammograms. The mammogram abnormalities such as masses are extremely difficult to identify because their radiographic and morphological characteristics resemble those of normal breast tissues. Since a digital mammogram is a projection image, mass lesions do not appear as isolated densities but as overlaid over parenchymal tissue patterns. Recently, many researchers in the field of mammography have been developed number of mammogram segmentation techniques. Various segmentation methods include, Region growing [4], Markov Random Fields [5], Fractal modeling [5], Tree structured wavelet transform [6], Adaptive density-weighted contrast enhancement [6], Morphological operations [3] and Dynamic programming based techniques.
Heuristics are determined from the characteristics of the segmented region of interests. The number of features during feature extraction and these heuristics are selected for early breast cancer detection. Image features are computed in different image domains, i.e., texture, spatial and morphological are extracted from mammogram images [1]. In feature extraction, key characteristics of the region of interests (ROIs) are extracted and analyzed which characteristics are useful to classification of malignant and benign tumors [8] (mass lesions) or micro-calcifications in further work of classification.
Segmenting the suspicious region from mammogram images and surrounding regions are carried out; it is useful for extraction of suspicious tissues of breast segments [15] to [17]. The feature extraction and building of classifier are similar to other pattern recognition systems.
Texture is one of the pattern based visual features that playing an important role in image processing[18]. Numbers of methods are used for texture feature extraction and it is more important in the analysis of medical images as well as automation of image-based applications[19]. The textures of images may carry useful information for detecting any unwanted things or suspicious regions. Various texture feature methods [1] are based on the gray-level values, levels of granularities of images etc.
ROI segmentation may useful for finding effective texture features and it has some limitation that it is more useful for training of small number of mammogram images for building models of breast cancer mammogram image. Effective training requires huge collection of mammogram images[20]. In such cases, it is required to extend ROI segmentation for supporting of training the large number of mammogram images. This proposed multi-ROI is discussed in the following section.

3. Multi-ROI Segmentation

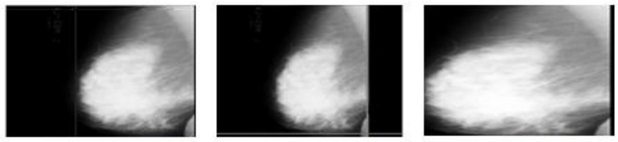
The basic functionality is common for both ROI and multi-ROI, however multi-ROI is an iterative version. Thus, it is flexible for selection of region of interests for large image datasets and it is faster technique. Fig. 1 shows the results of multi-ROI for sample mammogram images. Textual properties of segmented objects play a vital role for detection [14] of breast cancer or classification of abnormalities of mammogram images.
In multi-ROI framework, better model is evolved toward the boundary of selected region of interest and it is determined for modeling of interior intensity distribution of large collection of mammogram images[21]. Here, image intensity probability map is computed for a given set of mammogram images. Mean probability is calculated for a set of mammogram images and it is applied on image intensity probability map ‘PI’ for producing of a binary image ‘BPI’, whose pixels are higher than the threshold value ‘I’. binary mask of multi- ROI is ‘BIr’ and compute the shape image of ‘BIr’ and it is denoted as ‘ '. The multi-ROI intensity data term is defined as follows:

$$\mathrm{MROI(i)} = \frac{1}{n}\int\int(\phi_M(x) - \phi_r(N)).dx \quad (1)$$

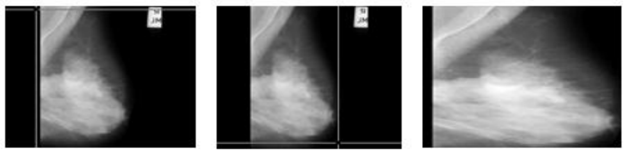
where 'n’ refers to total number of mammogram images, ‘ ' and denotes the overall shape or model mammogram images and shape of non-selected region of mammogram image ‘i’ respectively.
First-order and second-order statistics are used for measuring the texture properties of multi-ROI segmented mammogram images.
MROI (i) selected region of image of mammogram image ‘i’ over to shapes of mammogram images.



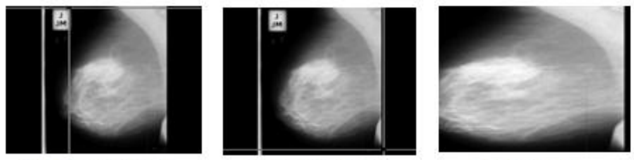
(a) Segmentation 1 (b) Segmentation 2 (c) ROI result
Fig. 1.1: Multi-ROI Segmentation Results for ‘ mdb001’ image in iteration 1



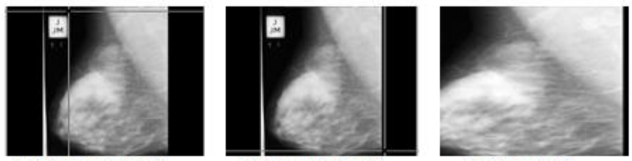
(a) Segmentation 1 (b) Segmentation 2 (c) ROI result
Fig. 1.2: Multi-ROI Segmentation Results for ‘mdb002’ image in iteration 2



(a) Segmentation 1 (b) Segmentation 2 (c) ROI result
Fig. 1.3: Multi-ROI Segmentation Results for ‘mdb003’ image in iteration 3



(a) Segmentation 1 (b) Segmentation 2 (c) ROI result
Fig. 1.4: Multi-ROI Segmentation Results for ‘mdb004’ image in iteration 4



(a) Segmentation 1 (b) Segmentation 2 (c) ROI result
Fig. 1.5: Multi-ROI Segmentation Results for ‘mdb005’ image in iteration 5

First-Order Statistics Based Texture Features

The relationships with neighborhood pixels are not considered in the first-order statistics [48], however these statistics computed from original values of the image and gives plenty of features based on image size I (x,y) with the size M x N. These include mean, standard deviation, kurtosis, skewness, and entropy and these are described in following equations (From Eqns. 2 to 6).

$$\mathrm{mean}(\mu) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y)}{MxN} \quad (2)$$

$$\mathrm{s\,tan\,dard\_deviation}(\sigma) = \sqrt{\frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y) - u}{MxN}} \quad (3)$$

$$\text{kurtosis} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y) - \mu^4}{MxNx\sigma^4} \tag{4}$$

$$\text{skewness} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y) - \mu^3}{MxNx\sigma^2} \tag{5}$$

$$\text{entropy} = \frac{1}{MxN}\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y)(-\ln(I(x,y)) \tag{6}$$

Second-Order Statistics based Texture Features

The second-order statistics [10] based on the relation between two neighboring pixels in one offset, where the first pixel is called the reference and the second the neighbor pixel. These include energy, contrast, variance, correlation, homogeneity. Energy describes the regularity feature of the image. It can be defined in Eqn. (7).

$$\text{energy} = \sum_{i,j=0}^{n-1} P(i,j)^2 \tag{7}$$

Here, the matrix element P(i,j) refers to the relative frequency of two pixels which are separated by a pixel distance (dx,dy) occur within a neighborhood with intensities of 'i' and 'j'. The variance of all pixels of mammogram image can be defined in Eqn. (8).

$$\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij}(i-\mu)^2 \tag{8}$$

The contrast computes the variation between lowest and highest values of a neighboring set of pixels and it shown in Eqn. (9)

$$\text{contrast} = \sum_{i,j=0}^{n-1} (i-j)^2 P(i,j) \tag{9}$$

The correlation shows how a pixel is correlated to its neighbor over the whole image. It shown in Eqn. (10)

$$\text{Correlation} = \sum_{i,j=0}^{n-1} \frac{(ixj)P(i,j) - \mu_i\mu_j}{\sigma_i\sigma_j} \tag{10}$$

Angular second moment (ASM) is used for measuring the homogeneity of a mammogram image and Eqn. (4.11) shows the homogeneity.

$$\text{Homogeneity} = \sum_{i=0}^{n-1}\sum_{j=0}^{n-1}\{P(i,j)\}^2 \tag{11}$$

4. Results Discussion

Multi-ROI is greatly support for obtaining of accurate texture features for large collection of mammogram images. In the experiments, initially we find the average models of two different types of mammogram images, namely, abnormal and normal [12] and then find the shape of non-selected region of i^{th} mammogram image. Shape of selected region is obtained by applying integrated difference of shape of mammogram model (for specific type of abnormal or normal mammogram image) and shape of non-region of selected mammogram image. Textual features are applied on resulting shape of selected mammogram of multi-ROI. Normal ROI [2] obtains the region of interest directly for selected mammogram image. Texture features of ROI and multi-ROI mammogram images are computed and presented in Table 1 for median filter segmented images, Table 2 for morphological segmented images, Table 3 for IMEM segmented mammogram images.

Table 1: Texture Values for Mammogram Images

Texture parameter	Name of the Image Enhancement Method Median Filter	
	Without Multi-ROI Pre-Processed Image	**Multi-ROI Pre-processed Image**
Mean	0.003491316	0.0038287
Standard Deviation	0.08973598	0.2512469
Entropy	2.96241	2.966462
Variance	0.008047196	0.008023004
Smoothness	0.912935	0.9324936
Kurtosis	12.01304	11.866092
Skewness	1.0039384	1.0681014
Contrast	0.2891548	0.2867634
Correlation	0.13448966	0.1517824
Engry	0.7973144	0.7891876
Homogeneity	0.9425092	0.9394728

Table 2: Texture Values for Mammogram Images

Texture parameter	Name of the Image Enhancement Method Morphological	
	Without Multi-ROI Pre-Processed Image	**Multi-ROI Pre-processed Image**
Mean	0.003491316	0.003368146
Standard Deviation	0.08973598	0.08974516
Entropy	2.96241	2.953132
Variance	0.008047196	0.00802452
Smoothness	0.912935	0.9180522
Kurtosis	12.01304	12.045874
Skewness	1.0039384	1.0752846
Contrast	0.2891548	0.2830924
Correlation	0.13448966	0.160724
Engry	0.7973144	0.7911768
Homogeneity	0.9425092	0.9406992

After observation of above tables, it is noted that texture features are improved in multi-ROI segmentation, since it uses multiple mammogram images for accurate shape features.

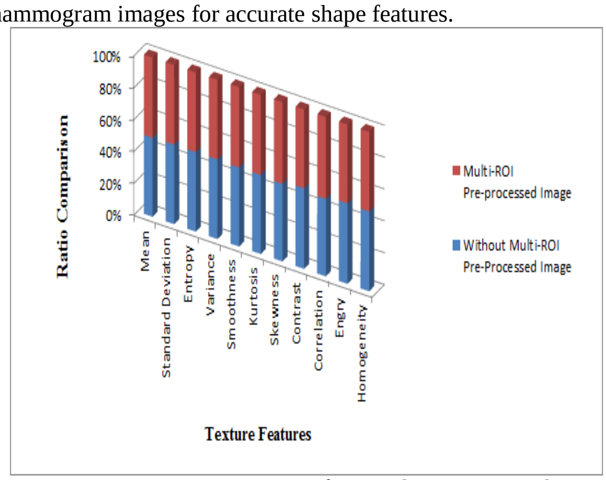


Fig. 2: Texture Features Comparisons for Wavelet Pre-Processed Images

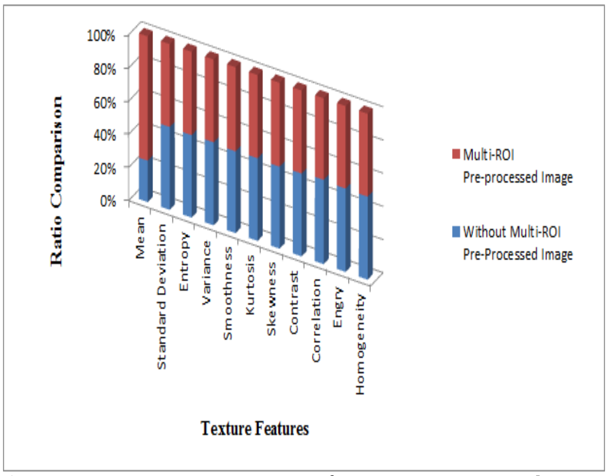


Fig. 3: Texture Features Comparisons for IMEM Pre-Processed Images

ROI and proposed multi-ROI segmentation are applied on wavelet transformation pre-processed and IMEM filtered image and their texture features are shown in Fig. 2 and Fig. 3 for the illustration of improvement of texture features in proposed multi-ROI method. From the experimental values of ROI and multi-ROI, it is investigated that multi-ROI is outperformed for accurate texture features. Textual properties of multi-ROI segmented images are highlighted visually in Fig. 2 and Fig.3 for the best illustration to breast cancer detection.

5. Conclusion

This paper is focused on mammogram segmentation and their texture features for breast cancer detection. Best illustration of texture features depends on segmentation results. Existing ROI segmentation performs the segmentation without knowledge of universal shape of mammogram model. Proposed multi-ROI segmentation used large collection of mammograms for deriving the universal shape (or average model parameters) of mammogram. It helps for getting accurate texture or shape features of suspected mammogram for breast cancer detection.

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