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Image Task Detection of Microcalcification on Mammogram

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Abstract: Texture analysis has been very much used in medical image problems as well as related areas such as computer vision and pattern recognition. Among all medical image task detection of microcalcification on mammograms is the most difficult one because breast cancer is the most prevalent cancer that leads to death in women today. More over microcalcification are deposits of calcium that can be seen in mammograms, which is the best way to detect breast cancer in the earliest stage and also to reduce death from breast cancer. Owing to the small size of micro calcification with a diameter of less than 0.5 mm level and are in the form of groups as clusters and in homogeneous back ground it is very difficult to detect. In this paper, we propose to develop a supervised texture mammography technique for image classification that includes supervised and unsupervised methods. In the unsupervised method for the detection of microcalcification, the prior information is required and in the case of supervised method information on microcalcification is very much needed for the processing. Previously many methods have been developed for the detection of microcalcification on mammogram. This paper analyses the texture analysis of mammography images using supervised and unsupervised classification methods and the results identifies that the unsupervised method has high accuracy than the supervised methods.

Key words: Microcalcification · Mammograms · Breast cancer · Texture classification

INTRODUCTION

The early detection of breast cancer is done by a special type of x-ray called mammography. The classification of calcium deposits into the affected and non affected categories is a difficult task, which includes the detection of tumors as suspicious regions with a weak contrast to their background and the extraction of features which characterize malignant tumors. Moreover the detection of masses in mammograms are too sensitive and so it is better to use the supervised and unsupervised classification methods in mammography images in order to describe of various discriminate characteristics of both true and false phenomenon from the areas. So far many researchers have gone for the mammography image classification. Li, H.D *et al* (13) proposed a new segmentation technique called modified Markov Random Field to detect the calcium deposit in digital mammography classification. Tughar Bhangale *et al* (14) proposed an unsupervised scheme for detection of microcalcification on mammograms with the help of K-Means clustering algorithm.

Our aim in this paper is to perform texture analysis on mammogram in both supervised and unsupervised methods. The comparative analyses have been done in terms of classification accuracy. In addition to the above contribution, the complete experiments done, that imparts the different similarity measures.

Existing Texture Analysis Methods

Texture Spectrum Operator: The local texture for a given pixel and its neighborhood is characterized by the corresponding texture unit and an image can be characterized by its texture spectrum in statistical approach for texture analysis which is the occurrence frequency function of all texture units within the image [2]. In a square raster digital image each pixel is surrounded by eight neighborhood pixels. The local texture information for a pixel can be extracted from a neighborhood of 3×3 pixels which is denoted by a set containing nine elements V= {v_0, v1……..v_8}, Where v_0 represents the intensity value of the central pixel and vi {I=1, 2,….8} is the intensity value of the

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neighboring pixel I) to define the corresponding texture unit by a set containing eight elements. Texture Unit (TU) = {E1, E2, E8} where E_I {i=1, 2, 8} is determined by the formula in equation 1.

$$Ei = \begin{cases} 0 \text{ if VI< VO} \\ 1 \text{ if VI=VO} \end{cases} 2 \text{ if VI>VO} \quad (1)$$

For i =1, 2, 8 and the element Ei occupies the same position as the pixel i. As each element of texture unit (TU) has one of three possible values with the combination of all eight elements results in 3^8=6561 possible texture units in total. Since there are three comparison levels (<, =,>) and have called this method as Texture Spectrum Operator. For N= 3, the combinations of all the elements results in 3^8=6561 possible texture units. There is no unique way to label and order the 6561 texture units that are labeled by using the formula in equation. 2.

$$NTU = \sum_{I=1}^{8} E_i \times 3^{i-1} \quad (2)$$

Where N_{TU} represents the texture unit number and Ei represents the element of the texture unit set TU= {E1, E2, E8}. For example, if eight elements are ordered clockwise as shown in Figure 1 and the first element may take eight possible positions from the top left to the middle left and then the 6561 texture units can be labeled by the above formula under eight different ordering ways from a to h.

In Figure 2, where the defined set of 6561 texture units describes the local texture aspect of a given pixel and its neighbors. Thus the statistics of the frequency of occurrence of an image should reveal texture information and texture spectrum is sensitive to the directional aspect of texture. The undesirable influence of the regional intensity background is eliminated from the texture spectrum. Here sample images from Mammographic Image Analysis Society (MIAS) data base have been taken and the optimal window size is selected for the further classification.

Entropy Based Local Descriptor: Entropy based local descriptor is a measure of information content which measures the randomness of intensity distribution. The entropy based local descriptor finds the average number of binary symbols needed to code a given input in terms of probability of that input appearing an a stream.

$$EBLD = \sum_{I=1}^{8} P(i) \log p(i) \quad (3)$$

A	B	C
H		D
G	F	E

Fig. 1: Eight Clock wise, successive ordering ways of eight element of the texture unit

Neighborhood ◄ Texture unit

63	28	15
88	40	35
67	40	21

2	0	2
2		0
2	1	0

V=(40,63,28,15,35,21,40,67,88), ◄TU=(2,0,2,0,0,1,2,2)
Texture Unit Number (NTU) = 6096

Fig. 2: Example of transforming a neighborhood to a texture unit with the texture unit number.

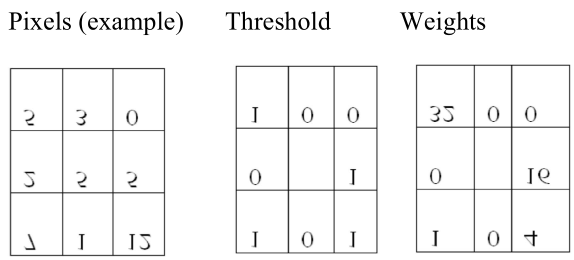

Fig. 3: Computation of Local binary patterns

Such a matrix corresponds to an image in which there are no preferred gray level pairs for the distance vector d. Entropy based local descriptor is highest when all entries in P [i, j] are of similar magnitude and small when the entries in P [i, j] are unequal. Entropy based local descriptor operator described with 2^8 possible textures and calculates the entropy of brightness in a local region of the picture. The entropy value is higher when the brightness in a local region of the picture is low and vice versa resulting the region seems to be small depending on the entropy value[7][11]. The main objective of Entropy based method is for the texture measure widely used to quantify the smoothness of image texture since Entropy does not depend on actual values in texture. High entropy based local descriptor is associated with a high variance in the pixel values, while low entropy based local descriptor indicates that the pixel values are fairly uniform. Here 60 sample images have been tested to detect the suspicious masses on mammographic images.

Local Binary Pattern Operator: In Local Binary Pattern Operator method uses the operators with eight neighboring pixels using the center as a threshold by multiplying the threshold values by weights given by powers of two [5, 6]. By definition Local Binary Pattern Operator shown in Figure 3 is invariant to any monotonic transformation of the gray scale and its quick to compute with larger neighborhoods, the number of possible Local Binary Pattern Operator codes increased exponentially. This can be avoided to some extent by considering only a subset of that codes and one approach is to use so called uniform patterns representing the statistically most Local Binary Pattern Operator.

The Local Binary Pattern operator shown in Figure 3 is determined by the formula is given in equation 4

$$\mathrm{LBP} = \sum_{I=1}^{8} E_i \times 2^{i-1} \tag{4}$$

Local Binary Pattern Operator does not take into account the contrast of texture which is the measure of local variations present in an image and is important in the description of some textures. Texture spectrum operator is similar to LBP Operator but it uses three levels that is, two thresholds instead of two levels used in Local Binary Pattern Operator. This leads to a more efficient representation and implementation than with Local Binary Pattern Operator and according to experimental tests with the help of varying the widow size for different same set of mammographic images that were used in TSO and entropy based methods.

Gray Level Co-Occurrence Matrices: Grey-level co-occurrence matrix (GLCM) is one of the most widely used statistical texture measures [12]. The idea of the method is to consider the relative frequencies for which two neighboring pixels are separated by a distance on the image. Since the GLCM collects information about pixel pairs instead of single pixels, it is called a second-order statistic. Texture measures, such as homogeneity, contrast and entropy are derived from the co-occurrence matrix. The different sets of images of MIAS have been tested and compared.

Texture Segmentation: In the view of detecting microcalcification on mammographic images our work has two parts namely segmentation and classification. The first part starts with the selection of unpreprocessed of size in three levels 128×128 256×256 and 512 ×512 which are then to be extracted in the form of detecting fine textural patterns. For the purpose of feature extraction here we have chosen Gabor filters. Since the mammographic images frequencies are lying in the band pass frequency levels that match with Gabor filter frequency. Once the images filtered are then to be subjected to a histogram based threshold in order to obtain binary images. The threshold (T) value can be found out by calculating the mean value which is to be added with the variance. Now the binary image is applied in the four mentioned texture analysis methods. The same set of procedure to extract the features from the mammographic images has been applied to the unsupervised classification to the method too using the K-means clustering algorithm. The methodology for the segmentation method is shown in Figure 4.

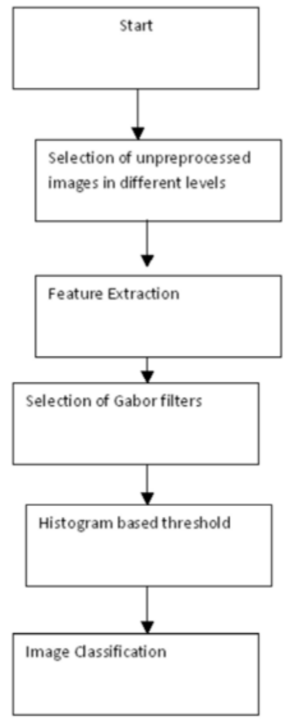

Fig. 4: Image Classification Procedure

Experimental Results and Analysis: Here Texture Spectrum Operator, Entropy Based Local Descriptor, Local Binary Pattern Operator and Gray Level Co occurrence Matrix has been evaluated for the same set of MIAS images. The results of classification accuracy have been computed and compared with the different texture images shown in Table 1. The classification accuracy for Texture Spectrum operator and Entropy Based Local Descriptor operator achieve less accuracy as compared

Table 1: Comparative analysis of different Classification methods

Different classification methods		Percentage of mass detection (Classification accuracy) %
Supervised classification methods	TSO	82
	EBLD	90
	LBP	92
	GLCM	93.5
Unsupervised classification methods	K-Means	95

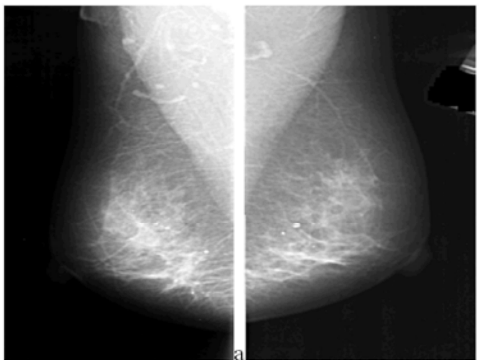

Fig. 5: Original mammogram

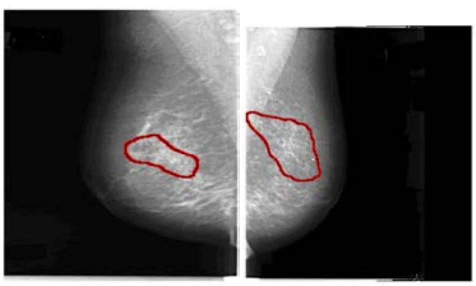

Fig. 6: Detected microcalcifications after texture analysis using GLCM and K- means clustering method

with Local Binary Pattern operator and Gray Level Co occurrence Matrix. But the unsupervised K-Means clustering method outperforms in terms of classification accuracy among all previous methods. In our investigation 60 breast classification images have been used and tested with both supervised and unsupervised methods to evaluate classification accuracy. The results show that the sensitivity has been 93.5% in classification accuracy through supervised method and 95% through unsupervised method. The Figure: 5 show the original mammography images and the Figure 6 shows the detected micro calcifications from the mammogram images for the supervised image classification.

From the Figure 7, it is clearly found that the classification accuracy of GLCM is overtaking other supervised methods. From the Figure 8, it is also clearly

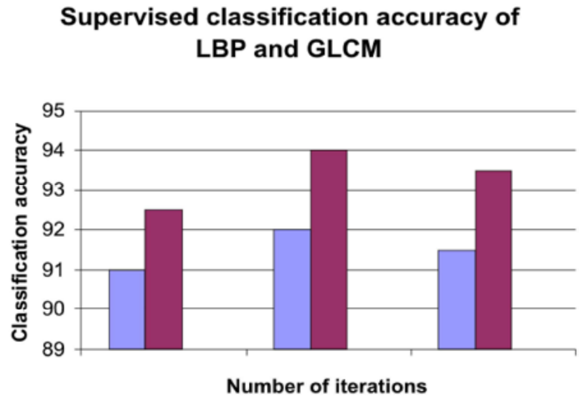

Fig. 7: Average supervised classification accuracy of LBP and GLCM

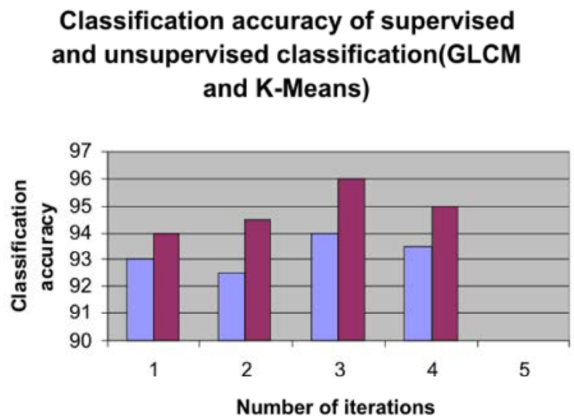

Fig. 8: Average classification accuracy of GLCM and K-Means method

identified that the classification accuracy of K-means method has higher classification accuracy than the GLCM and it is concluded that the unsupervised method is more suitable than the supervised method for the purpose of finding microcalcification on mammograms.

CONCLUSION

The images have been taken from the mammogram image analysis society (MIAS) for the validation of the proposed algorithm. The images used are having 512×512 pixels. Different sizes of range blocks chosen are 16×16, 32 ×32 and 64×64 pixels and the optimal value fixed is 16 to maximize the classification accuracy. The performance of the algorithm has been evaluated by calculating three parameters namely TP, FP and FN and it is found that the proposed algorithm is so attractive without compromising the classification accuracy.

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