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Orthogonal Features based Classification of Microcalcification in Mammogram using Jacobi Moments

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Abstract

Objective: Breast calcifications can be present in mammograms which are one of the most important risk indicators of breast cancer. Digital mammography is a reliable tool to detect breast cancer at the early stage with no symptoms. The objective of this research work is to classify the microcalcification patterns into benign and malignant. **Methods:** In this research, a novel approach is proposed for classification of microcalcifications based on shift-invariant transform, Jacobi moments and Support Vector Machines (SVM). The Jacobi moments are used to extract orthogonal features from the location of microcalcifications based on orthogonal or weighted polynomial basis which uses recurrence relation to avoid the loss of precisions. The Jacobi features will be given as input to SVM classifier for classifying the mammogram images into normal and abnormal. The abnormality will be further classified into benign or malignant. **Findings:** The validity of the proposed approach is evaluated using MIAS database. In the process of mammogram enhancement, the experimental results shows that shift–invariant transform achieves better results than contourlet transform. The classification rate of proposed system is 98.65% for normal, 95.80% for benign and 93.35% for malignant accuracy. The performance of the proposed approaches measured by sensitivity, specificity and confusion matrix. The measurement of performance is 0.84 sensitivity and 0.95 specificity for stage1 and 0.85 sensitivity and 0.83 specificity for stage 2. **Application/Improvement:** The results show that our proposed approach gives high level of accuracy for classification of microcalcification. This approach is very useful to avoid unnecessary biopsy.

Keywords: Breast Calcifications, Jacobi Moments, Orthogonal Features, Support Vector Machines

1. Introduction

Breast cancer arises due to uncontrollable nature of breast cells which produce a breast tumor. The breast tumor can be normal and abnormal. The normal tumor represents no cancerous. The abnormal consists of two classes such as benign and malignant. Benign tumors are not considered cancerous which is close to normal in appearance, they grow slowly, and they do not invade nearby tissues or spread to other parts of the body. Malignant tumors are cancerous. Left unchecked, malignant cells eventually can spread beyond the original tumor to other parts of the body. There are several kinds of abnormalities revealed such as asymmetrical breast tissue, asymmetrical density, architectural distortion, mass, microcalcifications, and interval changes compared with previous films, adenopathy and other miscellaneous. In the literature study deals with several abnormalities in microcalcifications. In which mammogram based microcalcification is used for this study. Microcalcifications are tiny mineral deposits within the breast tissue. This can be classified as either

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benign or malignant based on their characteristics such as size, distribution and shape.

Moments are powerful tool to capture significant features in the field of image processing which have been wide range applications such as in pattern recognition, image analysis, object representation, image reconstruction, classification of chromosomes and texture analysis[1–3]. In 1961, Hu[4] introduced utilization of moment invariants for image analysis and object representation which based on the theory of algebraic forms. The author derived invariant moment using nonlinear combination of geometric moments which has invariant to scaling, translation and rotation. The main drawback of this moment is not orthogonal, high information redundancy and image reconstruction is quite difficult. Teague[5] first introduced orthogonal moments based on theory of orthogonal polynomial such as Legendre and Zernike polynomials to overcome the problems associated with the geometric moments.

Orthogonal moments are powerful tool for many applications including image analysis and pattern recognition due to its orthogonal or weighted orthogonal polynomial basis. The use of generalized orthogonal moments leads to stable and fast numerical implementation, avoiding loss of precisions, more precise error estimates, improved image reconstruction and many more. Feature extraction is the essential step in the breast diagnosis which is used to acquiring higher level information of an image. There are several types of features have been proposed and developed in the medical image processing, especially in the breast diagnosis. Texture features are important which is used to differentiate mammographic regions. These features broadly classified into statistical, moment-based, form based, structural, and spectral features[6]. Support Vector Machine (SVM) is a group of supervised learning method that can be applied to classification or regression. SVM has been used wide range applications, such as in drug design, quantitative structure-activity relationships, chemometrics, sensors, chemical engineering, text mining[7], image classification, Hand-written characters classification and medical science.

During the breast mammography X–ray test, a glass dosimeter and spatial dose measuring meter was used to measure and evaluate the exposure dose and spatial dose distribution of each organs by exposure dose and scattered ray in order to obtain the optimal image for diagnosis and minimize the exposure dose[8]. Median filtering, normalization and modified tracking algorithm have been used for mammogram enhancement and performance is also enhanced by SNR[9]. A methodology based on fractal image modeling is developed to analyze and model breast background structures and set of parameters of affine transformations can be used to enhance microcalcifications[10]. Lalli, G et al.[11] has developed a computerized scheme for predicting early stage microcalcification clusters in mammogram images. The gray and color channels of a mammogram image are enhanced by Contrast Limited Adaptive Histogram Equalization (CLAHE). Optimal set of features selected by Genetic algorithm are fed as input to Adaptive Neuro-Fuzzy Inference System (ANFIS) for classification of images into normal, suspect and abnormal categories.

Statistical features are extracted from the Region of Interest (ROI) of the breast parenchymal region. The extracted features are fed into the K–NN classifier to classify the ROI into any of three breast tissue classes such as dense, fatty and glandular[12]. Artificial neural network is used to classify the mammogram images into normal and abnormal[19]. Ultrasound imaging is one of the most frequently used diagnosis tools to detect and classify abnormalities of the breast. In this method the masses are classified as either benign or malignant[13]. Orthogonal rotational invariant moments have been proposed to error analysis due to its invariant to rotation, scaling and translation and robust to noise[14].

Pew- Thian Yap et al.[15] have presented the set of moments which is based on Jacobi polynomials. The set of Jacobi polynomials are orthogonal and ensure minimal information redundancy between moments. By changing the parameters and , it is shown that the moments are able to extract local and global features. Jacobi polynomials have many well– known special cases of Legendre polynomials or spherical polynomials, Gegenbauer polynomials or Ultra spherical polynomials, Chebyshev polynomials of the first kind and Chebyshev polynomials of the second kind. Guo et al.[16] used generalized Jacobi polynomials/functions with indexes that they are mutually orthogonal with respect to the corresponding Jacobi weights and established two sets of approximation results by using the Sturm–Liouville operator and the derivative recurrence relations. This generalized Jacobi polynomials/functions leads to much simplified analysis, more precise error estimates and well–conditioned algorithms. Jacobi moments are presented to detect breast tumor in mammograms independent of their size, orientation and position[17].

2. Materials and Methods

There are various approaches existing for classification of microcalcifications. The forthcoming subdivisions describe the mathematical background of Jacobi moments and methodologies to achieve better performance.

2.1 Microcalcification Enhancement

The mammogram images are noise, low-contrast and blur due limitations of X-ray hardware systems. The detection of microcalcifications is difficult due to their small shapes and size and also exhibits poor contrast which is enhanced by shift-invariant transform[18].

2.2 Jacobi Moments

Jacobi moments are set of moments which are framed by set of Jacobi polynomials. This moment helps to extract both local and global features of microcalcifications in mammograms which also include the properties of both local moments and global moments.

2.3 Jacobi Polynomials

Jacobi polynomials are set of orthogonal polynomials which are the special cases of Legendre polynomials, Gegenbauer polynomials, Chebyshev polynomials of the first kind and Chebyshev polynomials of the second kind. This polynomial provides information redundancy between moments.

The Jacobi polynomial of n^{th} order is computed as[15]

$$J_n^{\alpha,\beta}(x)=\frac{(\alpha+1)_n}{n!}\times{}_2F_1\left(\begin{matrix}-n,n+\alpha+\beta+1\\ \alpha+1\end{matrix}\middle|\frac{1-x}{2}\right) \quad (1)$$

Where $x \in [-1,1]$.

The general hyper geometric function ${}_rF_s$ is defined by

$${}_rF_s\left(\begin{matrix}a_1,\dots,a_r\\ b_1,\dots,b_s\end{matrix}\middle|z\right)=\sum_{k=0}^{\infty}\frac{(a_1,\dots a_r)_k}{(b_1,\dots b_r)_k}\frac{z^k}{k!} \quad (2)$$

Where $(a_1,\dots a_r)_k=(a_1)_k,\dots,(a_r)_k$

and $(b_1,\dots b_s)_k=(b_1)_k,\dots,(b_s)_k$

The Pochhammer symbol is defined as

$$(a)_n=a(a+1)(a+2),\dots\dots,(a+n-1)=\frac{\Gamma(a+n)}{\Gamma(a)} \quad (3)$$

Where $n=1,2,3,\dots$ and $(a)_0=1$ and thus have the explicit expression

$$J_n^{\alpha,\beta}(x)=\frac{\Gamma(\alpha+n+1)}{n!\Gamma(\alpha+\beta+n+1)}\sum_{m=0}^{n}\binom{n}{m}\frac{\Gamma(\alpha+\beta+n+m+1)}{\Gamma(\alpha+m+1)}\left(\frac{x-1}{2}\right)^m \quad (4)$$

Jacobi polynomials can be defined by Rodrigues' formula

$$J_n^{\alpha,\beta}(x)=\frac{(1-x)^{-\alpha}(1+x)^{-\beta}}{(-2)^n n!}\frac{d^n}{dx^n}\left[(1-x)^{n+\alpha}(1+x)^{n+\beta}\right] \quad (5)$$

Where $\alpha,\beta>-1$.

The Jacobi weigh function can be defined as

$$\omega^{\alpha,\beta}(x)=(1-x)^{\alpha}(1+x)^{\beta} \quad (6)$$

The Jacobi polynomials are orthogonal and satisfy the following condition

$$\int_{-1}^{-1}J_n^{\alpha,\beta}(x)J_m^{\alpha,\beta}(x)\omega^{\alpha,\beta}(x)dx=\gamma_n^{\alpha,\beta}\delta_{n,m} \quad (7)$$

Where $\delta_{n,m}$ is the Kronecker delta and

$$\gamma_n^{\alpha,\beta}=\frac{2^{\alpha+\beta+1}}{2n+\alpha+\beta+1}\times\frac{\Gamma(n+\alpha+1)\Gamma(n+\beta+1)}{\Gamma(n+1)\Gamma(n+\alpha+\beta+1)} \quad (8)$$

The Jacobi polynomials are defined by the recurrence relation

$$\begin{aligned}&2n(n+\alpha+\beta)(2n+\alpha+\beta-2)J_n^{\alpha,\beta}(x)=(2n+\alpha+\beta-1)\\&\{(2n+\alpha+\beta)(2n+\alpha+\beta-2)x+\alpha^2-\beta^2\}J_{n-1}^{\alpha,\beta}(x)\\&-2(n+\alpha-1)(n+\beta-1)(2n+\alpha+\alpha+\beta)J_{n-2}^{\alpha,\beta}(x),\end{aligned} \quad (9)$$

Where

$$n = 2,3,4....;\ J_0^{\alpha,\beta}(x) = 1,\ J_1^{\alpha,\beta}(x) = \frac{1}{2}(\alpha+\beta+2)x + \frac{1}{2}(\alpha-\beta)$$

The Moment based orthogonal features are extracted by Jacobi moments. The Jacobi moments are orthogonal which is based on set of Jacobi polynomials. The Jacobi moment of order (p + q) of an image f (x,y) with M×N pixels is defined as

$$J_{mn} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \bar{J}_m(x) \bar{J}_n(x) \tag{10}$$

Where $\bar{J}_m(x) \equiv \bar{J}_m^{\alpha_1,\beta_1}(x)\ \bar{J}_n(y) \equiv \bar{J}_n^{\alpha_2,\beta_2}(y)$

And

$$\bar{J}_n^{\alpha,\beta}(x) = J_n^{\alpha,\beta}(x)\sqrt{\frac{\omega^{\alpha,\beta}(x)}{\gamma_n^{\alpha,\beta}}} \tag{11}$$

So that

$$\sum_{x=0}^{N-1} \bar{J}_m^{\alpha,\beta}(x) \bar{J}_n^{\alpha,\beta}(x) = \delta_m \tag{12}$$

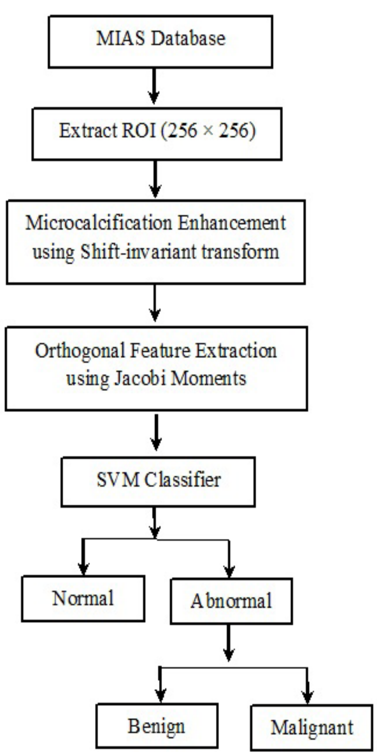

Figure 1. Proposed classification of microcalcification system.

3. Proposed Method

This section focuses microcalcification classification system based on shift–invariant transform and Jacobi moments. An overview of the proposed classification of microcalcification approach is shown in Figure 1. First, the mammogram ROI (256 × 256) is extracted from MIAS database then shift-invariant transformis applied to enhance the mammograms. In this transform, pixels are classified into three types such as strong edges, weak edges and noise. This transform retains the coefficients of strong edges, amplifies the coefficients of weak edges and zeros to noise edges. This shift–invariant transform ensures perfect reconstruction after modifying coefficient which distinguishes noise edges and weak edges.

Among the various orthogonal moments, the Jacobi moment is selected as features extractor due to its ability to extract both local and global features and robustness to image noise. In this work, Jacobi moments are orthogonal or weighted polynomial which uses recurrence relations to avoid the loss of precision. First, normal and abnormal areas are identified and separated from complete image. Jacobi moments are used to extract orthogonal features from the location of microcalcification area. In the second step, SVM classifier is used against different training set to classify the mammogram into normal and abnormal. Eventually the abnormality is classified into benign and malignant.

4. Experimental Results

This research work is experimentally shown using MATLAB2014a and MIAS database. The MIAS database contains 204 normal images and 118 abnormal images belong to both benign and malignant. Out of which, this study considers 194 normal and 25 microcalcifications images for experiments. First, the selected images are enhanced by shift–invariant transform. Figure 2 shows the sample normal, benign and malignant enhanced images. The performance of the proposed enhancement is compared with contourlet transform and evaluated by PSNR. The experimental results for normal, benign and malignant are shown in Table 1, Table 2 and Table 3 respectively.

The performance of the proposed system has been evaluated by using classification rate in percentage and number of training and testing used in the classification phase is given Table 4 and the classification rate obtained

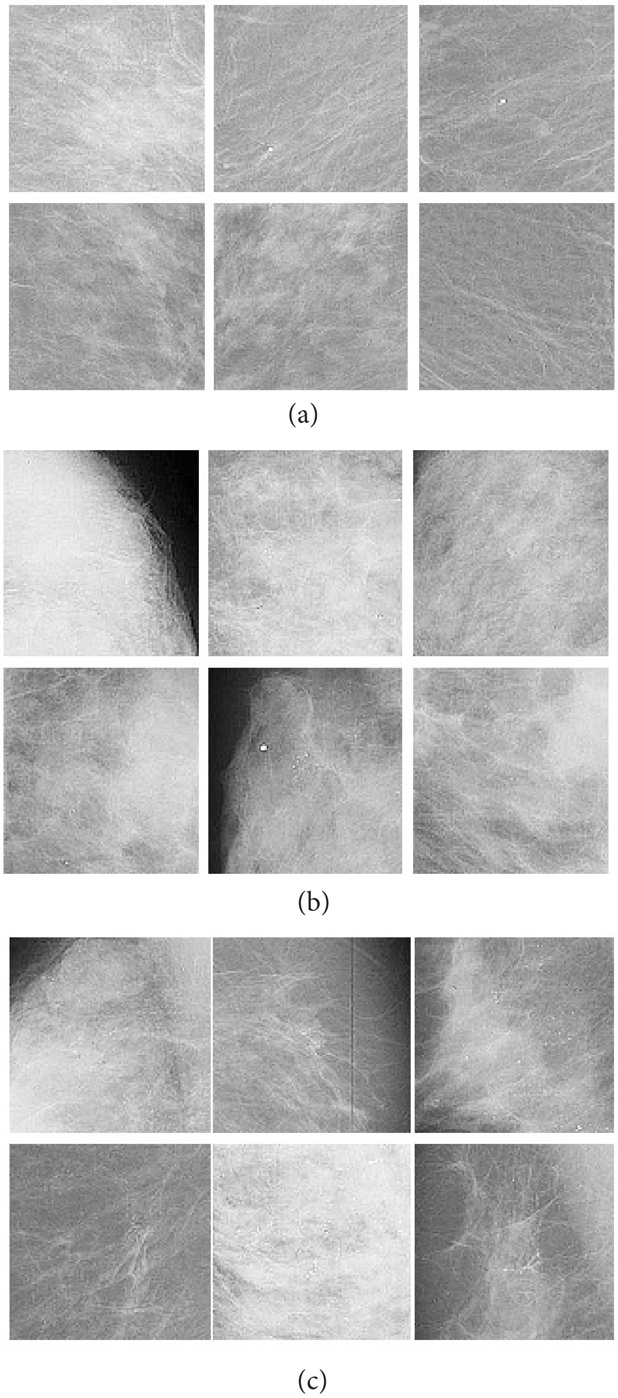

Figure 2. Sample enhanced images: a) Normal b) Benign and c) Malignant.

using Jacobi features are shown in Table 5 and right columns results were obtained[16]. In this work, the researchers did not consider microcalcification enhancement and recurrence relation to extract features. Confusion matrix for normal and abnormal and benign and malignant is

Table 1. PSNR performance for normal images

Image ID	PSNR	
	Contourlet Transform	Shift-invariant Transform
mdb003	22.5487	28.9640
mdb004	13.4674	29.1752
mdb006	17.6157	28.8629
mdb007	14.1626	29.8792
mdb009	9.3751	29.8836
mdb011	8.5530	29.4042
mdb014	9.7560	29.1337
mdb016	15.7172	29.9657
mdb020	10.6820	29.4538
mdb022	20.2297	29.8154

Table 2. PSNR performance for benign images

Image ID	PSNR	
	Contourlet Transform	Shift-invariant Transform
mdb218	19.6595	23.1318
mdb219	23.9105	30.0747
mdb222	13.1795	29.8268
mdb223	23.5938	30.0281
mdb226	12.5827	29.5107
mdb227	23.7035	29.7172
mdb236	13.0941	29.2286
mdb240	24.7206	28.9506
mdb248	13.3594	29.5699
mdb252	25.3190	29.9438

Table 3. PSNR performance for malignant images

Image ID	PSNR	
	Contourlet Transform	Shift-invariant Transform
mdb209	13.2597	30.1508
mdb211	10.9647	29.9983
mdb213	21.8809	29.7778

mdb216	15.9516	29.1889
mdb231	14.5418	29.5537
mdb238	24.9372	30.5567
mdb239	18.0971	29.3514
mdb241	25.8627	29.3098
mdb245	18.0787	29.6508
mdb249	24.008	30.081

Table 4. Number of Training and Testing samples

Types of images	No. of training Images	No. of testing Images
Normal	120	74
Abnormal	15	10
Benign	7	5
Malignant	8	5

Table 5. Classification Result of the proposed system

Types of images	% Classification Rate	% Classification Rate[16]
Normal	98.65	87.63
Abnormal	96.25	84.00
Benign	95.80	83.33
Malignant	93.35	84.62

Table 6. Confusion matrix for normal and abnormal classifier (Stage 1)

Test Outcome	Condition	
	Abnormal	Normal
Abnormal	21	9
Normal	4	185

Table 7. Confusion matrix for benign and malignant classifier (Stage 2)

Test Outcome	Condition	
	Malignant	Benign
Malignant	11	2
Benign	2	10

Table 8. Sensitivity and Specificity for the classifier stages

Classifier stages	Sensitivity	Specificity
Stage 1	0.84	0.95
Stage 2	0.85	0.83

shown in Table 6 and Table 7 and Table 8 show the sensitivity and specificity for the classifier.

It is easy to observe that from the Table 8, for the classifier stages, the sensitivity is obtained as 0.84 for stage 1 and 0.85 for stage 2. Similarly, the specificity is obtained as 0.95 for stage 1 and 0.83 for stage 2. Also, it is identified that the classification results is very high for normal type of images and it is less for malignant type of patterns from the Table 5.

5. Conclusion

In this research work, a novel approach is proposed for classification of microcalcification in mammograms. In mammogram enhancement, the images are enhanced for the clear identification of microcalcifications from whole image. The shift–invariant transform gives shift–invariant multiscale and multidirection property which provides perfect reconstruction after modifying coefficient. This transform gives better performance than contourlet transform. Jacobi moments use recurrence relation to extract orthogonal features from the location of microcalcification area only. Ultimately, this research work comes up with better fine–tuned results on classification of microcalcifications using mammography. Our future work is extended to detect abnormalities in digital mammograms using discrete moments.

6. References

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