An Adaptive Behavioral Learning Technique based Bilateral Asymmetry Detection in Mammogram Images

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Abstract

Objectives: This work is used to efficiently analyze and identify the sign of the Bilateral Asymmetry presence in the mammogram images. Methods/Statistical Analysis: The proposed work performs the feature selection process prior to the classification of mammograms as Bilateral Asymmetry and architectural distortion. For the Bilateral Asymmetry the features used are based on the directional, morphological and density. For selecting potential features Artificial Bee Colony Optimization (ABCO) technique is used. The performance of each feature set obtained is measured using Artificial Neural Network classifier. The dataset for analysis is collected from MIAS database. Findings: The results of the ANN classification obtained by using the feature selection Particle Swarm Optimization and Ant Colony Optimization with the three features $M_1$, $M_2$ and $H$ aligned are selected but its performance is relatively low while comparing with the selected features of the ABCO. The ABCO significantly reduces the false positive rates in the detection of the ROI in the Bilateral Asymmetry detection. In recognizing the sign of bilateral asymmetry, the results retrieved shows best performance which indicates features of directional features and ROI alignment. The experimental result shows that in the Bilateral Asymmetry the sensitivity and specificity using PCO is 0.79% and 0.83% and for ABCO it is 0.89% and 0.91% respectively. So the rate of true positive value increases in a substantial manner thus reducing the false positive rate. Application/Improvements: In this study, prelude results are exposed related to the segmentation of fibro-glandular discs, the two angular distributions categorizations and the features extraction. It reports the detection of Bilateral Asymmetry in Mammogram images that may be used by radiologists for earlier prediction of breast cancer. Future work will address the problem of the asymmetry assessment.

Keywords: Artificial Bee Colony Optimization, Artificial Neural Network Classification, Behavioural Learning, Bilateral Asymmetry Detection, Directional Feature Extraction, Morphological Feature Extraction

1. Introduction

Worldwide Breast cancer is the best part persistent of all cancers and is the primary reason for cancer deaths of women in India. It accounts for 27% of women with all types of cancers. A legitimate report tells that 1 out of 28 women are accountable to build up breast cancer at any stage in their lifetime. In urban areas, 1 out of 22 women are accountable to build up breast cancer through her life span and as evaluated to the rural areas, 1 in 60 women are pretentious of breast cancer. Mammography acts as the most efficient image modality tool for early detection of the breast cancer. Screening mammography lessen the mortality rates by 30% to 70%. The precision of elucidation of screening mammograms is exaggerated by numerous factors, such as quality of the image, expertise in the field of the radiologist's and the high degree of cases. To detect the sign of breast cancer in an early
stage, digital mammographic method acts as one of the well-known inspection methods. This method is used for the complete review process of the patient in suspect. This method reveals the prominent abnormalities such as masses, macrocalcifications, Bilateral Asymmetry and architectural distortion. Figure 1 shows the three symptoms of the breast cancer in the mammogram.

Figure 1. Three different signs of breast cancer in Mammogram.

- Masses: Breast cancer leads to a desmoplastic effect in the breast tissue. A mass is observed as a bright, hyper-dense object.
- Calcification: It indicates the calcium deposits in the breast tissue.
- Bilateral Asymmetry: Differences in the overall appearance of one breast with reference to the other.

The paper presents a technique for recognition of the critical sign of the breast cancer namely Bilateral Asymmetry. The proposed work spots out the presence of the Bilateral Asymmetry in the mammogram. It combines the directional, morphological and geometric features related to the distributions of the density of the tissue. In this work some earlier researches made in the detection of the Bilateral Asymmetry is recapitulated. The proposed method adapts an Artificial Bee Colony Optimization for the feature selection in the Bilateral Asymmetry detection. This is exemplified with a step by step procedure. The paper also presents the performance assessment of the proposed method with the existing approaches and draws conclusions and future work.

2. Literature Review

There are very few related algorithms which are designed and implemented for the Bilateral Asymmetry detection. The very first step namely registration or alignment process detects the Bilateral Asymmetry and it is a tedious task. Due to the nature of the asymmetry in the breasts, radiologists miss to find the fine points in achieving match of left and right breast images and also deformation intrinsic to breast images. Linear directional components for the Bilateral Asymmetry detection were offered. The Gabor filter is used for producing the Gabor Wavelet with the help of the multi-resolution. It uses different scales and orientation.

Algorithms and methodologies were designed with the aid of the CAD to identify both the morphological and anatomical asymmetry. It produces an efficient result using the assessment of normal pairs. B-spline interpolation using computer-aided detection algorithm for the breast alignment was also presented. Colored images are presented as result and shown on a display device. This result is used by radiologists for an extra investigation procedure. A computerized process for the Bilateral Asymmetry discovery was adapted that consists of the mammography density analysis. Bilateral Asymmetry is detected using Gabor filters and classification is performed using linear Bayes classifier. These methods are used to identify the degree of asymmetry of the two breasts. A new technique for registration of Bilateral Asymmetry based on anatomical features and a premise for deformation of breast images was proposed. The work establishes an anatomical coordinate system which is used to divide breast into an upper and a lower parts. Differential analysis is performed by proposing two methods. The former technique identifies the absolute difference between registered images and the later proves the geometric differences between neighborhoods. Only few researches have been done with Bilateral Asymmetry detection techniques without registration and alignment process of breasts. Integration of morphological measures and statistical moments of fibro-glandular disk is the extension of work done in the scheme of linear directional components. With the aid of the rose diagrams discrimination directional feature are mined and with the help of segmented fibroglandular disks the further set of features are taken out. To examine the asymmetry between the left and right mammogram images the distinction between
the pairs of the features are used as measures. There exist many classification algorithms like Alternating Decision Tree (AD Tree), Best First Tree (BF Tree) and Neuro Fuzzy methods\textsuperscript{12,18}. In the prior analysis of the asymmetry in the mammograms preprocessing is essential to eliminate the parts in the mammogram which do not contain significant information.

3.1 Preprocessing

In this paper we have adapted our previous work methodology for preprocessing mammogram images and it consists of two different stages namely breast region extraction and pectoral muscle extraction. The Figure 3 shows that in the first stage the background is eliminated for extracting breast region alone from the given input image using low pass filter followed by extracting pectoral muscle using non-linear diffusion method.

Figure 3. Block diagram of Mammogram two stage preprocessing.

![Figure 3](image)

Algorithm for the breast region extraction

**Input:** Test image of mammogram

**Procedure: Stage 1**

**Steps:**
- Select the input image of the mammogram
- Perform normalization by applying the histogram equalization on the input image
- Transform the image into a Fourier transform
- Apply the low pass filter using the convolve with a mask
- Compute Threshold on the grayscale image
- All the pixels with the grey level value less than the threshold are marked as the background and the rest as the breast
- Extract the Breast Contour part alone

**Output:**

Extracting Breast Contour

Figure 4. Algorithm for the breast region extraction.

![Figure 4](image)

The algorithm for the breast region extraction is explained in the Figure 4 and the pectoral muscle detection and elimination are described in the Figure 5.

3.2 Spatial Fuzzy C-means Clustering Technique for Fibro-glandular Segmentation

In the traditional Fuzzy C-means algorithm for a pixel \( x_k \) \( I \) where \( I \) is the image, the clustering of the \( x_k \) with cluster \( C_i \) depends on the distance measure between \( x_k \) and the center of the cluster \( C_i \). Since the clustering process is...
related to the histogram of the image and does not take into account of any spatial information, the FCM algorithm is sensitive to the noise and other artifacts\textsuperscript{[12,13]}. 

Algorithm for the Pectoral Muscle Extraction

**Input:** Test image of the breast region alone of the mammogram obtained through stage 1

**Procedure:** Stage 2

Steps:
After obtaining the breast border from stage 1 define ROI using 5 control points N1 to N5
N1: top-left corner pixel of the breast contour.
N2: top-right corner pixel of the breast contour.
N5: lowest pixel on the left edge of the boundary
N3: mid-point between N1 and N5;
N4: the point that completes a rectangle with N1, N2, and N3
Perform the following steps until the iteration reached
Apply Gaussian filter on the selected ROI
Calculate Gradient of the ROI
Perform the Non-Linear diffusion function using the diffusivity function as follows:

\[
D(x,t) = 1 - \exp\left(-\frac{C_m}{\lambda}\right) \frac{U(x,t)}{m}
\]

After iteration gets completed perform thresholding on the image to extract pectoral muscle

**Output:**
Extracting pectoral muscle region

Figure 5. Algorithm for the pectoral muscle extraction.

One of the important characteristics of the real-world images is that the neighboring pixels usually have strong correlation between them. In the other words, if the pixel \( x_k \) belongs to the cluster \( C_i \), then its neighbors exists in a window around it. It should have similar and high membership values in \( i^{th} \) clustering. Therefore, in the paper, spatial FCM algorithm called SFCM is adopted to improve the performance and also to overcome the limitation of the standard FCM algorithm. In the SFCM algorithm, the clustering is done using a new membership function based on the spatial neighborhood information. In the Figure 6 the algorithm for fibroglandular disc segmentation is discussed.

3.3 Feature Extraction

Five directional features i.e. first \( (M_1) \) and second \( (M_2) \), angular moments, entropy \( (H) \) and dominant orientation \( (\theta_\phi) \) are extracted from the difference rose diagrams, as follows:

\[
M_1 = \bar{\theta} = \frac{\sum_{i=1}^{\phi} \theta_i}{\phi} \quad \theta_R = \arctan \frac{Y_R}{X_R}
\]

\[
M_2 = \sum_{i=1}^{\phi} R_i [\theta_i - \bar{\theta}]^2 \quad \varphi_1 = (m_{20} - m_{02})
\]

\[
\varphi_2 = (m_{20} - m_{02})^2 + 4m_{11}^2
\]

\[
H = -\sum_{i=1}^{\phi} R_i \log_2 [R_i] \quad \varphi_3 = (m_{30} - 3m_{12})^2 + (3m_{21} - m_{30})^2
\]

\[
X = \sum_{i=1}^{\phi} R_i \cos \theta_i \quad \varphi_4 = (m_{20} - m_{12})^2 + (m_{20} + m_{12})^2
\]
The Figure 7 shows the original images of the left and right breast mammogram images. After applying the rose diagram the results are shown. The orientation is obtained after applying the Gabor filter and klt transform and then displays the rose diagram of the aligned mammograms. The next step is enhancing the contrast to detect the dissimilar part and the dissimilar part is identified by finding the difference between the original rose diagram and processed rose diagram. The affected region is shown in the green line. The affected part alone is extracted.

In the ABC algorithm, the food source acts as the solution for the optimization problem and the quality of the associated solution is represented as the nectar amount. The number of the employed bees or the onlooker bees is equal to the number of the solutions in the population.

The main steps of the algorithm are as below:

Main Steps for the algorithm on the Artificial Bee Colony Optimization

- Population value is initialized.
- Do.
- On the food sources the employed bees are placed.
- Depending on the nectar amount place the onlooker bees on the food sources.
- To discover new food source the scouts bees are send.
- Remember the best food source found determine so far.
- until requirements are met.

In the Artificial Bee Colony method there are three parameters that act as the control parameters: The first control parameter (SN) is the food source that is based on the employer bees (SN). The employer bees are also called as the onlooker bees. The second parameter is the limit value. The third parameter represents the Maximum Cycle Number (MCN). In the honeybees’ structure, the rate of the recruitment of the onlooker bees depends on the speed with which the bee colony finds and takes the control in the newly discovered food source. The recruitment process occurs artificially based on the measurement of the speed with which better quality solutions can be identified for the difficult optimization problems. If there exists best food resource, then the survival and progress of the bee colony results in the rapid discovery and efficient utilization. The real time difficult problems of the engineering depend on the fast discovery of the good solutions. Exploration and acquiring of the food sources are carried out hand in hand in parallel for the robust search process. When the scouts control the exploration process, the exploitation is carried out by the onlookers and employed bees in the ABC algorithm. Detailed pseudo-code of the ABC algorithm is given in the Figure 8.

Algorithm for Artificial Bee colony Optimization

1. Initialize Cycle =1
2. Assign values for Artificial Bee Colony algorithm input parameters
3. Calculate the fitness of each individual feature
4. Do
5. Develop solutions by the employed bees
   Initialize feature subset configurations to every employed bee
   Construct new feature subsets \( V_i \)
   Pass the constructed feature subset to the classifier
   Estimate the fitness \( (fit_i) \) of the feature subset

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\[ \text{fit}_i = 1 + \frac{1}{1 + e^{-x_i}} \]

Compute the probability \( p_i \) of feature subset solution

\[ p_i = \frac{\text{fit}_i}{\sum_{i=1}^{n} \text{fit}_i} \]

6. Creat4 solutions by the onlookers
Pick a feature based on the probability \( p_i \)
Create the new solutions \( V_i \) for the onlookers from the solutions \( x_i \) selected depending on \( P_i \) and evaluate them employ the greedy selection process for the onlookers

7. Find the abandoned solution for the scout, if available, and replace it with a new randomly produced solution \( x_i \) by

\[ X_i^j = X_i^j + \text{rand}[0,1] \times (X_{\text{max}}^j - X_{\text{min}}^j) \quad (3) \]

8. Memorize the best solution achieved so far
9. cycle = cycle + 1
10. until cycle = MCN

**Figure 8.** Pseudocode for ABC algorithm.

### 4. Experimental Results

To show the results of the proposed work, the data set is used from MIAS database and implemented using MATLAB. To evaluate the proposed technique 36 cases are taken from the Mini-MIAS database, out of which 14 cases are with the abnormality of Bilateral Asymmetry and 22 are ordinary cases.

#### 4.1 Evaluation Metrics

In this study, prelude results are exposed related to the segmentation of fibro-glandular discs, the two angular distributions categorizations, and the features extraction. Future work will address the problem of the asymmetry assessment. A univariate analysis is performed to estimate the performance of every feature for the asymmetry assessment. This analysis is done to reveal this performance in terms of Sensitivity and Specificity.

\[ \text{Sensitivity} = \frac{TP}{TP + FN}, \]
\[ \text{Specificity} = \frac{TN}{TN + FP} \]

Where:
- True Positive is that the algorithm has reported that a pair of mammograms was identified to have asymmetry in the left or right breast which was also the report given by an expert radiologist.
- False Positive is that algorithm reports a pair of normal mammograms to be asymmetric.
- True Negative is that the algorithm reports a pair of normal mammograms as normal.
- False Negative is that the algorithm reports a pair of mammograms to be normal which was identified by an expert radiologist to have asymmetry.
- Precision is the probability that a (randomly selected) retrieved rule is relevant.
- Recall is the probability that a (randomly selected) relevant rule is retrieved in a search.
- F-Measure is a measure that combines precision and recall is the harmonic mean of precision and recall, the traditional F-measure or balanced F-score.

Precision recall and F-measure are defined as:

\[ \text{Precision} = \frac{tp}{tp + fp} \quad \text{Recall} = \frac{tp}{tp + fn} \]

\[ F = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \]

### 4.2 Performance Analysis of Proposed Bilateral Asymmetry

Table 1 shows the most significant features used for features selection in Bilateral Asymmetry detection using the Artificial Neural Networks (ANN).

#### Table 1. Performance comparison of the proposed Bilateral Asymmetry detection using ABCO based feature selection and existing approaches with ANN as classifier

<table>
<thead>
<tr>
<th>Feature Selected</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>M, not aligned</td>
<td>0.75</td>
<td>0.82</td>
</tr>
<tr>
<td>M, H aligned</td>
<td>0.74</td>
<td>0.69</td>
</tr>
<tr>
<td>M, M, H</td>
<td>0.72</td>
<td>0.76</td>
</tr>
<tr>
<td>( \phi, DA, DD )</td>
<td>0.65</td>
<td>0.68</td>
</tr>
<tr>
<td>( \phi, \phi, \phi, DA, DD )</td>
<td>0.57</td>
<td>0.60</td>
</tr>
<tr>
<td>PSO with M, M, and H features Selected, aligned</td>
<td>0.79</td>
<td>0.83</td>
</tr>
<tr>
<td>ACO with M, M, and H features selected, aligned</td>
<td>0.82</td>
<td>0.84</td>
</tr>
<tr>
<td>ABCO with M, M, H and ( \theta ) features selected, aligned</td>
<td>0.89</td>
<td>0.91</td>
</tr>
</tbody>
</table>
The feature set $M_1$ not aligned, $M_2$, $H$ aligned and $M_1$, $M_2$, $H$ are belonging to the directional features which are extracted from the rose diagram which shows the results of the Bilateral Asymmetry classification of the cases that are considered here. Using ABCO technique finest overall classification was obtained, which produced 89% sensitivity and 91% specificity with four features $M_1$, $M_2$, $H$ and $\theta_R$ with the alignment.

The sixth and seventh row of Table 1 presents the results of the ANN classification obtained by using the feature selection Particle Swarm Optimization and Ant Colony Optimization with the three features $M_1$, $M_2$ and $H$ aligned are selected but its performance is relatively low while comparing with the selected features of the ABCO. The rate of false positives got considerably reduced using ABCO algorithm in detecting ROI for Bilateral Asymmetry detection. All the results obtained are compared and analysed. This analysis reveals that best results were produced in the detection of Bilateral Asymmetry when directional features along with alignment were referenced in ROI. The Figure 9 shows the proposed outcome of the Bilateral Asymmetry detection.

The Figure 9 shows that the maximum area under curve is performed by the ABCO than the other two techniques.

5. Results and Discussions

In Bilateral Asymmetry detection the vital sign of it is determined by proposing three different phases in this methodology. They are extraction of features, selection of features and classifying it. The comparison of analogous anatomical regions between the left and right breast are used for extraction of features. To list the oriented structures the directional angular data is used on both right and left mammograms. To find the difference between morphological measures and geometric moments of fibro-glandular disks is another significant analysis. The obtained results are compared and examined reports reveals that the directional features together with alignment with the sign to the boundaries of pectoral muscle, give the optimum consequences in the acknowledgment of the bilateral asymmetry. These effects maintain the predictable declaration that the directional information associated with fibro glandular tissue consistency is a more imperative method to detect Bilateral Asymmetry when compared to the density or morphological features of the breast. For feature selection the ABCO has the highest performance with the specificity of 0.89 and sensitivity of 0.91 of the selected features using ANN classification.

6. Conclusion

In this paper the methodology for the analysis of Bilateral Asymmetry in mammogram images is obtained. In the Bilateral Asymmetry the directional, morphological and density features are taken into the account. From the results obtained using the detection of the Bilateral Asymmetry with the help of feature extraction using the ABCO with the four selected features and classification of the presence of the Bilateral Asymmetry using the Artificial Neural Network classification it produces better result in their sensitivity and specificity with other existing approaches that is PSO and ACO. The experimental result shows that in the Bilateral Asymmetry the sensitivity and specificity using PCO is 0.79% and 0.83% and for ABCO it is 0.89% and 0.91% respectively. So the rate of true positive value increases in a substantial manner thus reducing the false positive rate.

7. References


