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SHAPE FACTORS FOR ANALYSIS OF BREAST TUMORS IN MAMMOGRAMS

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Abstract: Distinguishing between benign and malignant breast tumors requires careful analysis of their shape complexity and radiographic definition. In this paper we examine the usefulness of shape factors such as compactness, moments, Fourier descriptors, and statistics of chord lengths in distinguishing between circumscribed/ spiculated and benign/ malignant masses. A database of 54 tumors was used in pattern classification experiments. Classification accuracies of 95% for circumscribed/ spiculated, 76% for benign/ malignant, and 77% for four-group classification were obtained, which indicate the usefulness of the proposed methods in breast cancer diagnosis.

1 Introduction

Recent statistics show that approximately one in ten Canadian women will develop breast cancer in their lifetime [1]. Although curable, especially when detected at early stages, breast cancer is expected to account for 28% of incident cancer cases and 20% of cancer deaths in women [1]. Studies have shown that early detection of breast cancer through periodic mammographic screening of asymptomatic women can reduce breast cancer mortality. Mammography is currently not only the most sensitive and specific method for detecting breast cancer, but also the most practical technique for screening and follow up [2].

The several types of breast abnormalities which are visible in mammograms include asymmetry between the breasts, distortion in the architecture of the breast, increase in breast tissue density, masses, and calcifications [3, 4]. Masses are examined for location, shape, density, size, and their margins. Higher density is usually an indicator of malignancy, while lucent-centered lesions are usually benign. Cancerous lesions generally have a more irregular shape than benign lesions. Masses may be circumscribed, spiculated, or stellate in shape. Circumscribed lesions are compact and roughly elliptical. Spiculated lesions usually have a blurred boundary and radiating appearance [3]. Stellate lesions have an irregular appearance and are surrounded by a radiating pattern of linear spicules.

In this article, we investigate the use of shape factors using moments, Fourier descriptors, chord length statistics, and compactness based upon contours of masses, as well as moments based upon density distributions to aid in classification of tumors and masses. We consider both two-group classification as circumscribed/ spiculated or benign/ malignant, as well as four-group classification as circumscribed benign (CB), circumscribed malignant (CM), spiculated benign (SB), and spiculated malignant (SM). The features are evaluated by pattern classification experiments using the leave-one-out algorithm and the Mahalanobis distance procedures in the BMDP (Biomedical Programs) software package [5].

2 Images and Databases

Thirty-nine images including 16 CB, four CM, 12 SB, and seven SM biopsy-proven tumors were selected from the Mammographic Image Analysis Society (MIAS, UK) database. The images have an optical density (OD) range of 0-3.2 with 8 bits per pixel and a spatial resolution of $50\ \mu\text{m} \times 50\ \mu\text{m}$.

In order to augment the CM and SM numbers, fifteen images from Screen Test: Alberta Program for the Early Detection of Breast Cancer with three CM and 12 SM biopsy-proven tumors were included to form a combined database. The Screen Test images have a dynamic range of 0.02-2.52 OD at 8 bits per pixel and a pixel size of about $62\ \mu\text{m} \times 62\ \mu\text{m}$.

Sections of interest of the mammographic images were displayed on a Sun SPARCstation 2 and the boundary of each tumor region of interest (ROI) was traced and input to the computer by an expert radiologist specialized in mammography (JELD) using the XPAINT software for X Windows. This step of manual input of the tumor boundary was chosen in this work as the aim here is to analyze the effectiveness of the proposed measures of shape roughness in classifying tumors, rather than detection of tumors.

3 Shape Analysis

3.1 Moment-based Shape Factors

Various moments may be computed from an object's silhouette or boundary; the former approach is less sensitive to noise and is an indicator of gross shape, while the latter is more sensitive to high-frequency edge details. The two-dimensional (2D) $(p+q)^{th}$ -order moment m_{pq} of an object is defined as

$$m_{pq} = \sum_i \sum_j i^p j^q I(i,j) \qquad p,q = 0,1,\cdots, \qquad (1)$$

where the summation is over all pixels in the ROI silhouette or boundary, $I(i,j)$ is the image intensity at the pixel (i,j). The object centroid is defined as $(\bar{x} = m_{10}/m_{00}, \bar{y} = m_{01}/m_{00})$ [6].

As tissue density usually reduces as one moves outwards at the boundaries of malignant tumors, we computed a variation of the moments as a function of the absolute difference of the gray level of each pixel in the ROI with respect to the average gray level of the ROI $\bar{I}$ as

$$m'_{pq} = \sum_i \sum_j i^p j^q |I(i,j) - \bar{I}| \qquad p,q = 0,1,\cdots. \quad (2)$$

Levine [6] indicated that the centroidal profile, which is a plot of the distance z_i from the centroid to each boundary point in sequence, may be normalized to the maximum distance and used as a shape descriptor. This technique, in which a shape is characterized by a one-dimensional sequence, has been used by Gupta and Srinath [7] for classifying closed planar shapes. We have proposed a new shape factor $MF_{1-3} = F_1 - F_3$ based upon low-order moments F_1 and F_3 given as [8]

$$F_1 = \frac{1}{m_1}\sqrt{\frac{1}{N}\sum_{i=1}^{N}(z_i - m_1)^2}\,, \qquad (3)$$

$$F_3 = \frac{1}{m_1}\left[\frac{1}{N}\sum_{i=1}^{N}(z_i - m_1)^4\right]^{\frac{1}{4}}, \qquad (4)$$

where N is the number of boundary pixels and $m_1 = 1/N\sum_{i=1}^{N} z_i$. Note that this measure is independent of pixel intensity. We have applied this shape factor to analysis of mammographic calcifications; results indicated excellent correlation of this feature with the roughness of the calcifications and robustness with respect to variations in object size, rotation, and translation.

Hu [9] (see also Levine [6] for details) derived a set of seven low-order, central invariant moments, which are functions of the second- and third-order central moments:

$$\begin{aligned}
M_1 &= \mu_{20} + \mu_{02}\,, & (5)\\
M_2 &= (\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2\,, & (6)\\
M_3 &= (\mu_{30} - 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2\,, & (7)\\
M_4 &= (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2\,, & (8)\\
M_5 &= (\mu_{30} - 3\mu_{12})(\mu_{30} + \mu_{12})[(\mu_{30} + \mu_{12})^2 - 3 & \\
&\quad (\mu_{21} + \mu_{03})]^2 + (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03}) & \\
&\quad [3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2]\,, & (9)\\
M_6 &= (\mu_{20} - \mu_{02})[(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] & \\
&\quad +4\mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03})\,, & (10)\\
M_7 &= (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12})[(\mu_{30} + \mu_{12})^2 - 3 & \\
&\quad (\mu_{21} + \mu_{03})^2] - (\mu_{30} - 3\mu_{12})(\mu_{21} + \mu_{03}) & \\
&\quad [3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2]\,. & (11)
\end{aligned}$$

where $\mu_{00} = m_{00} = \mu$, $\mu_{10} = \mu_{01} = 0$, $\mu_{20} = \mu_{20} - \mu\bar{x}^2$, $\mu_{11} = \mu_{11} - \mu\bar{x}\bar{y}$, $\mu_{02} = \mu_{02} - \mu\bar{y}^2$, $\mu_{30} = \mu_{30} - 3\mu_{20}\bar{x} + 2\mu\bar{x}^3$, $\mu_{21} = \mu_{21} - \mu_{20}\bar{y} - 2\mu_{11}\bar{x} + 2\mu\bar{x}^2\bar{y}$, $\mu_{12} = \mu_{12} - \mu_{02}\bar{x} - 2\mu_{11}\bar{y} + 2\mu\bar{x}\bar{y}^2$, and $\mu_{03} = \mu_{03} - 3\mu_{02}\bar{y} + 2\mu\bar{y}^3$. Size normalization is achieved by dividing each of the factors by μ^γ, where $\gamma = 1 + (p+q)/2$.

In this work, the shape factors listed above were computed for each tumor ROI to obtain the set MF_{1-3}, M^{bd}_{1-7}, M^{b}_{1-7}, M^{rd}_{1-7}, M^{r}_{1-7}, and $M^{rd'}_{1-7}$ computed as follows: MF_{1-3} were computed using equations (3-4); M^{bd}_{1-7} were obtained using equations (1) and (5-11) using only the ROI boundary pixels with their grey level values; M^{b}_{1-7} are similar ro M^{bd}_{1-7} but do not use the grey level values; M^{rd}_{1-7} were obtained using all the pixels within the ROI along with their grey level values in equations (1) and (5-11); M^{r}_{1-7} were obtained as M^{rd}_{1-7} but without the grey level values; and $M^{rd'}_{1-7}$ were obtained using all the pixels within the ROI along with their grey level values in equations (2) and (5-11). Here, the superscript b denotes use of boundary pixels only, d denotes use of grey level or density, r denotes use of the entire region, and $'$ denotes use of the difference in grey level with respect to the ROI mean as in equation (2).

The invariant moments M_1 to M_7 are not independent of object contrast, and are numerically sensitive. However, the methods have been applied successfully to automatic recognition of aircraft types [10].

3.2 Chord Length Statistics

Discrimination of 2D closed shapes using their chord length distribution was discussed by You and Jain [11]. A chord L_i is defined as a line segment which links a pair of boundary points, normalized by the length of the longest chord. The complete set of chords for a given object consists of all possible chords drawn from every boundary pixel to every other boundary pixel. You and Jain [11] consider the $K = N(N-1)/2$ chord lengths of the N boundary points of an object as a sample distribution set and compute Kolmogorov-Smirnov (K-S) statistics as dissimilarity measures. The technique was applied to boundary maps of seven countries and six machine parts with different levels of resolution, and the results indicated good discrimination between shapes. The chord method is invariant to size, translation, and rotation, and is stable with respect to noise. Shape features may be computed from chord distributions as

$$M_{c1} = \frac{1}{K}\sum_{i=1}^{K} L_i\,, \quad (12)$$

$$M_{c2}^2 = \frac{1}{K}\sum_{i=1}^{K}(L_i - M_{c1})^2\,, \quad (13)$$

$$M_{c3} = \frac{1}{M_{c2}^3}\frac{1}{K}\sum_{i=1}^{K}(L_i - M_{c1})^3\,, \quad (14)$$

$$M_{c4} = \frac{1}{M_{c2}^4}\frac{1}{K}\sum_{i=1}^{K}(L_i - M_{c1})^4\,. \quad (15)$$

3.3 Fourier Descriptors

It has been indicated that the multi-channel model of the human visual system may be employed for shape analysis: the low-frequency channels provide information regarding the general shape, whereas the higher-frequency channels indicate aspects of boundary details [6]. Lin and Chellappa [12] showed that classification based on FDs is accurate even when 20-30% of the data are missing.

In the computation of FDs, the (x, y) coordinates of each point in the periodic array of the N boundary points of an object are represented as complex values, given by $Z_i = x_i + jy_i\,; i = 0, 1, \cdots, N-1$. The FDs are defined as

$$A(n) = \frac{1}{N}\sum_{i=0}^{N-1} Z_i exp[-j2\pi ni/N] \quad n = 0, \cdots, N-1 \quad (16)$$

Using only the magnitude of the FDs, normalized FDs (NFDs) may be obtained as [8] $NFD(k) = 0$ for $k = 0; NFD(k) = A(k)/A(1)$ for $k = 1, \cdots, N/2; NFD(k) = A(k+N)/A(1)$ for $k = -1, \cdots, -N/2+1$. Emphasizing low-frequency components, we derived an FD-based shape factor (FF) as [8]

$$FF = 1 - \frac{\sum_{k=-N/2+1}^{N/2} ||NFD(k)||/||k||}{\sum_{k=-N/2}^{N/2} ||NFD(k)||}\,. \quad (17)$$

The advantage of this measure is that it is not sensitive to noise, which would be caused if weights increasing with frequency were used. FF becomes larger as the object shape becomes more complex and rough, and is limited to the range (0, 1). FF is invariant to translation, rotation, starting point, and contour size, and we have successfully applied it to shape analysis of mammographic calcifications [8].

3.4 Compactness

Compactness C is a simple measure of contour complexity versus the enclosed area, defined as $C = p^2/a$, where p and a are the object perimeter and area respectively. A shape with a rough contour possesses a high C value, indicating low compactness. In order to restrict the range of C to (0, 1), and to obtain increasing values with increasing shape complexity or roughness, we use the modified definition [8] $C = 1 - 4\pi a/p^2$. The modified compactness value is zero for a circle.

4 Results of Pattern Classification

The shape factors C, FF, MF_{1-3}, M_{1-7}^{bd}, M_{1-7}^{b}, M_{1-7}^{rd}, M_{1-7}^{r}, $M_{1-7}^{rd'}$, and M_{c1} to M_{c4}, were computed for each tumor or mass for use as features in pattern classification. The BMDP "7M" step-wise discriminant analysis program [5] was used to find the combination of variables that best predicts the group to which each case belongs. The 7M program performs a jack-knife validation procedure (leave-one-out algorithm). It computes the Mahalanobis distance to each group mean and the posterior probabilities of belonging to each group. Then, it classifies each case into the group with the highest posterior probability according to classification functions computed from all data except the case being classified.

Circumscribed/ Spiculated Classification: The best circumscribed/ spiculated classification rates of 94.9% for the MIAS database and 94.4% for the combined database were obtained using the combination M_{c1} to M_{c4}, C, FF, and MF_{1-3}. The simple measure of compactness alone gave a high accuracy of 92.3% with the MIAS database, but a lower rate of 88.9% with the combined database. The combination of M_{1-7}^{bd} and M_{1-7}^{b} gave a high circumscribed/ spiculated classification rate of 92.3% for the MIAS database set. The chord length features gave, on their own, circumscribed/ spiculated classification rates of 79.5% and 87% for the two databases.

Benign/ Malignant Classification: The shape measures that depend on boundary information only, namely C, FF, MF_{1-3}, M_{1-7}^{b}, and M_{c1} to M_{c4} in different combinations gave benign/ malignant classification rates of no more than 69.2% and 75.9% for the two databases. The shape factors M_{1-7}^{r} based upon the whole ROI but not including the density did not fare any better than the shape factors based on boundary information only as above. Addition of information on boundary pixel or ROI density to the shape factors in computing M_{1-7}^{bd}, M_{1-7}^{rd}, and $M_{1-7}^{rd'}$ did not provide benign/ malignant classification accuracies of more than 74.5% for the MIAS database and 70.4% for the combined database. Further, the chord-length measures did not fare any better than the other shape measures.

Four-group Classification: The best four-group (CB, CM, SB, and SM) classification rates of 76.9% for the MIAS database and 68.5% for the combined database were obtained using the combination M_{c1} to M_{c4}, C, FF, and MF_{1-3}. The moment-based measures including the ROI density information did not provide any better rates than simpler measures such as C and FF acting alone.

5 Discussion

Characterization of mammographic masses and tumors and their classification has been a difficult problem. In this paper we have analyzed the effectiveness of a number of well-known shape factors in distinguishing between different types of tumors. The simple measure of compactness provided a high level of accuracy in circumscribed/ spiculated classification with a rate of 92.3% for the 39 MIAS cases. More complex shape measures based on Fourier descriptors and moments did not give any higher rates of accuracy. While shape factors based on chord length statistics did not perform well on their own, they contributed in combination with compactness, Fourier descriptors, and moment-based shape factors to achieve high rates of about 95% accuracy with the 39 MIAS cases as well as the combined database of 54 cases.

The shape factors provided limited accuracies in the neighborhood of 75% for benign/ malignant and four-group classification. Although some of the moment-based shape factors studied in this work take into account density variations within the tumor ROI, they do not specifically consider the differences in edge definition between benign and malignant tumors. In order to address this shortcoming, we are proposing a measure of edge profile acutance which is based on adaptively-computed directional derivatives along normals to the ROI boundary and represents boundary fuzzyness of the ROI [13].

Acknowledgements

This project was supported by grants from the Natural Sciences and Engineering Research Council (NSERC) of Canada and the Alberta Breast Cancer Foundation. We thank the Embassy of the Arab Republic of Egypt, Cultural and Educational Bureau, Washington D.C., USA, for the scholarship awarded to NME.

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