

CLASSIFICATION OF MAMMOGRAPHIC MASSES USING FUZZY INFERENCE SYSTEM

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ABSTRACT Computer aided detection (CAD) intends to provide assistance to the mammography detection, reducing breast cancer misdiagnosis, thus allowing better diagnosis and more efficient treatments. In this work the task of automatically classifying the mass tissue into Breast Imaging Reporting and Data System (BI-RADS) shape categories: round, oval, lobular, irregular and also as benign or malignant is investigated. Various geometrical shape and margin features based on maximum and minimum radius of mass are used in this work to classify the masses. These geometric features are found to be good in discriminating regular shapes from irregular shapes. For the purpose of classification, the masses are segmented from the mammogram using gray level thresholding. Prior to segmentation, the mammographic images are pre-processed using techniques like filtering and contrast enhancement. Finally, the classification is performed using fuzzy inference system that is constructed using MATLAB Fuzzy logic toolbox. The fuzzy rules are used to construct the generalized fuzzy membership function for classifying the shape and severity of masses. The images were collected from Mammographic Image Analysis Society (MIAS) Database and Digital Database for Screening Mammography (DDSM). The experiments were implemented in MATLAB.

Keywords: Gray level Thresholding, Fuzzy inference system, Classification, BI-RADS categories, Fuzzy rules.

INTRODUCTION

Breast cancer is considered a major health problem in western countries, and constitutes the most common cancer among women in the European Union (Eurostat, 2002). A recent study developed by the American Cancer Society estimates that, in the United States, between one in eight and one in twelve women will acquire breast cancer during their lifespan (American Cancer Society, 2007). Breast cancer remains, in the United States as well in the European Union, the leading cause of death for women after their 40 s (Eurostat, 2002; Buseman et al., 2003). However, although breast cancer incidence has increased over the past decade, breast cancer mortality has declined among women of all ages (Sickles, 1997). This positive drift in reduction of mortality may relate to the extensive acceptance of mammography screening (Sickles, 1997; De Koning et al., 1995), and improvements made in breast cancer therapy (Buseman et al., 2003).

Mammography is considered as the main screening method for the detection of abnormalities present in breast. However, it is known that even skilled radiologists can miss a considerable amount of abnormalities (Bird et al., 1992; Birdwell et al., 2001). In addition, after biopsy a great number of mammographic abnormalities end up being benign (Basset and Gold, 1987; Hall et al., 1988).

There are a large number of different types of mammographic abnormality. In the majority of cases, however, the abnormalities are either micro-calcifications or masses. Micro-calcifications usually form clusters and individual micro-calcifications can range from 20 to several hundred microns in diameter. On the other hand, a breast mass is a generic term to indicate a localized swelling, protuberance, or lump in the breast. Masses can be caused by different processes: from natural changes in the breast to cancerous processes. Masses are characterized

by their location, size, shape, margin, and associated findings (i.e. architectural distortion, contrast). The associated properties are examined by radiologists as they are strongly correlated with the classification (benign versus malignant) of the mass (Heywang-Kobrunner et al., 2001). It is generally accepted that mass detection is a more challenging problem than the detection of micro-calcifications, not only for the large variation in size and shape in which masses can appear in a mammogram but also because masses often exhibit poor image contrast (Basset and Gold, 1987; Vyborny and Giger, 1994).

The idea of developing computer systems to assist radiologists in the detection and classification of breast cancer is not recent (Winsberg et al., 1967). However, the recent development of full field digital mammographic imaging systems has been a catalyst in the increase of such computer systems (Kuzmiak et al., 2002). A Computer-Aided Diagnosis (CAD) system is a set of automatic or semi-automatic tools developed to assist radiologists in the detection and/or classification of mammographic abnormalities (Birdwell et al., 2001; Freer and Ulissey, 2001). In medical viewpoint, interpreting mammograms visually is considered to be a very demanding job for radiologists. Their judgments essentially depend on the training, experience and subjective criteria. It is observed that 65–90% of the biopsies of suspected cancers turned out to be benign. Thus, it is essential to develop CAD that can distinguish benign and malignant lesions effectively. In CAD based systems, feature extraction and selection is an important part of supervised classification. The number of features selected for breast cancer detection varies with different CAD approaches employed. It is desirable to use an optimum number of features, since large number of features will increase computational needs, making it difficult to define accurate decision boundaries in a large dimensional space. It is proved from several studies that the CAD reasonably improves breast cancer diagnostic accuracy rate by 14.2%.

It is established that the shape and margin properties can be used for effectively classifying the masses. However, there exists impreciseness and ambiguity in describing the shape and margin of each mass in mammogram. It is known that fuzzy logic is a tool by which the ambiguity and impreciseness can be captured using suitable membership function. In this paper, various shape and margin properties for capturing the shape and margin properties of the masses are used. For each mass, all these properties are treated as feature and suitable membership function is proposed to capture the category of shape and category of masses.

METHODOLOGY

Mammogram pre-processing

Mammograms are medical images that are hard to interpret, thus in order to improve the image quality, pre-processing phase is needed and this will help in making the segmentation results more precise (Samir Kumar Bandyopadhyay, 2010). In this work, the pre-processing stage includes three steps. The first step involves the removal of labels and artifacts present in the mammogram. In order to detect these regions, an algorithm that uses a thresholding technique is implemented. So, the breast region alone is extracted for further processing. The second process is denoising the mammogram images. Digital mammography images often contain significant amount of noise. This noise should be removed for avoiding deterioration of the contrast enhancement algorithm and negative influence on the whole detection procedure. Therefore, median filter is used to de-noise the image. Median filter is a

non-linear filter having the ability to remove noise without blurring the edges. So it especially is a powerful tool for improving mammogram images (Gajanand Gupta, 2011). And finally, enhancement is applied as the third pre-processing step to the digital mammogram. In this work, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used for enhancing the mammogram images. The steps involved in pre-processing are given in Fig.1



Fig.1 Mammogram pre-processing

Mammogram segmentation

Mass segmentation is a quite difficult task because masses are often varying in size, shape and density. Masses can exhibit a very poor image contrast or can be highly connected to the surrounding parenchymal tissue. Thus, it is hard in many cases to distinguish the mass from the non-uniform normal breast tissue (Hajar Moradmand, 2011). Due to the high variability in the appearance of masses, generalizing a segmentation algorithm able to handle many different types of masses is a non-trivial task and much efforts have already gone through this issue.

In this paper gray level thresholding is applied to segment the masses from mammographic images. The gray level thresholding is a global technique and is based on the global information, such as the histogram. Since the masses are brighter than the surrounding tissues, it makes thresholding a useful method for segmentation (Moumena Al-Bayati and Ali El-Zaart, 2013). The regions with abnormalities will have added peaks on histogram while a healthy region has only one peak. After a global thresholding value is attained, the objects can be separated from the background.

In an image, when the intensity distributions of objects and background pixels are sufficiently distinct, it is possible to use a single (global) threshold applicable over the entire image. In most applications, there is usually enough variability between images that, even if global thresholding is a suitable approach, an algorithm capable of estimating automatically the threshold value for each image is required. The gray level thresholding uses an iterative algorithm which consists of the following basic steps.

Step 1: Select an initial estimate for the global threshold, T

Step 2: Segment the image using $g(x, y) = f(x) = \begin{cases} 1, & \text{if } f(x, y) > T \\ 0, & \text{if } f(x, y) \leq T \end{cases}$ which will produce two groups of pixels

G_1 consisting of all pixels with intensity values $> T$ and G_2 consisting of all pixels with values $\leq T$

Step 3: Calculate the mean intensity values m_1 and m_2 for pixels in G_1 and G_2

Step 4: Compute a new threshold value: $T_{new} = \frac{1}{2}(m_1 + m_2)$

Step 5: Repeat steps 2-4 until the mean values in successive iterations do not change

Mammogram Feature extraction

The third stage of mass detection by CAD (computer aided diagnosis) schemes is the feature extraction and selection. The features can be calculated from the ROI characteristics such as the size, shape, density, and smoothness of borders, etc. Some redundant features should be removed to improve the performance of the classifier. In this paper, shape features, also called the morphological or geometric features, are used for classifying the masses.

i) Mass Shape Characteristics According to BIRADS mass shape characteristics, benign masses tend to have round, oval, lobular in shape and malignant masses are lobular or irregular in shape. Measuring regular and irregular shapes using mathematical tool is found to be a difficult task, since there is no single measure to differentiate various shapes. In general, the masses are classified into 4 categories such as round, oval, lobular and irregular. Classifying masses into 4 categories is a challenging issue compared to classifying benign vs. malignant. Thus, it is appropriate to note that only shape characteristics can be used to discriminate these 4 categories. The Fig.3 shows the mass shapes of mammogram specified by BIRADS. Benign masses have round and oval shapes with circumscribed margin. It is noticed that benign masses are circular and convex in shape. Malignant masses have irregular shape with ill-defined, microlobulated or spiculated margins and malignant masses are irregular non-convex shapes (B. Surendiran and A.Vadivel, 2012).

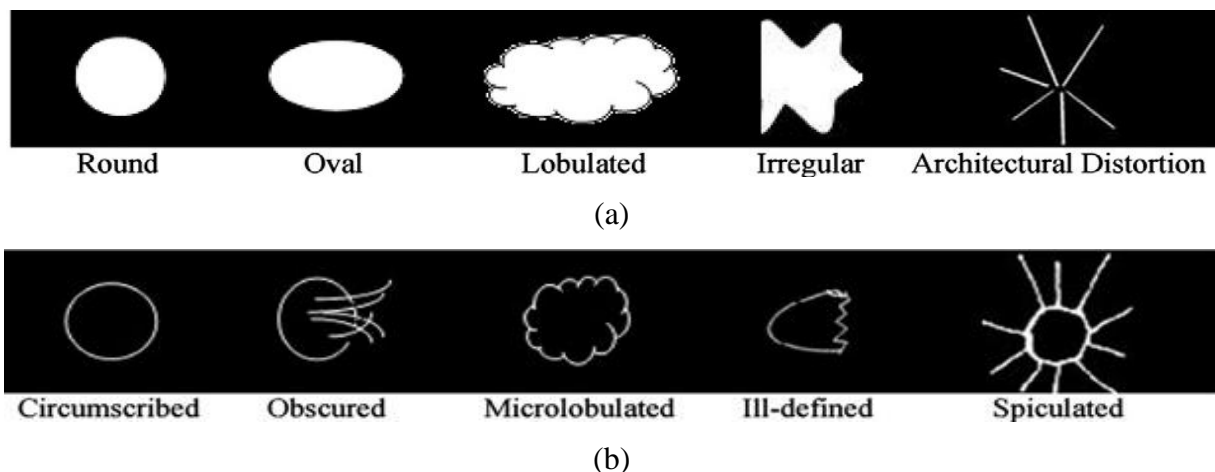


Fig.2 Various well-known shapes and margin (a) mass shapes (b) mass margins.

ii) Shape Properties The standard morphological features such as area, perimeter, equivalent diameter and few others can be found in (A. Rojas and A.K. Nandi, 2008). In this work, various other features like minimum and maximum radius, Compactness, Circularity1, Circularity2, Dispersion and Shape Index are also used.

Mammogram Classification

Automated classification of mammogram images is an increasingly important tool for physicians in their daily activity. The classification process involves grouping objects into pre-defined classes or finding the class to

which an object belongs. In this work, several features are extracted from the mammographic masses and given as the input for the classifier. The fuzzy inference system is used as the classifier to classify the shape and severity of the mass.

Fuzzy Inference System

A fuzzy inference system (FIS) is a rule-based system that uses fuzzy logic, rather than Boolean logic, to reason about data. In this work, fuzzy inference system is constructed using Matlab Fuzzy logic toolbox. The mamdani based fuzzy inference model is used for constructing rules. For defuzzification process, the centroid of the output fuzzy membership function is considered. The triangular membership function is used for constructing FIS in Matlab and is given in Eq.1.

$$\mu_A(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{b-x}{c-b}, & b \leq x \leq c \\ 0, & c \leq x \end{cases} \quad (1)$$

Even though rules can be generated using other features, the most suitable rule set for classification is selected. Maximum of 3–10 different sets of rules are generated for classification. The fuzzy inference system that is constructed using MATLAB Fuzzy logic toolbox is shown in Fig.3. For clarity, few rules are shown below

1. If (Dispersion $\leq v_1$) and ($w_3 \leq$ Perimeter $\leq w_4$) and ($x_2 \leq$ Equivdiameter $\leq x_3$) and (Circularity2 $\leq y_1$) then (Mass_type is Irregular)
2. If ($v_1 \leq$ Dispersion $\leq v_2$) and ($w_2 \leq$ Perimeter $\leq w_3$) and ($x_3 \leq$ Equivdiameter $\leq x_4$) and ($y_1 \leq$ Circularity2 $\leq y_2$) then (Mass_type is Oval)
3. If ($v_2 \leq$ Dispersion $\leq v_3$) and ($w_1 \leq$ Perimeter $\leq w_2$) and ($y_2 \leq$ Circularity2 $\leq y_3$) then (Mass_type is lobular)
4. If ($v_3 \leq$ Dispersion $\leq v_4$) and (Perimeter $\leq w_1$) and (Equivdiameter $\leq x_1$) and ($y_3 \leq$ Circularity2 $\leq y_4$) then (Mass_type is Round)

where v_1, v_2, v_3, v_4 are the values of Dispersion, w_1, w_2, w_3, w_4 are the values of Perimeter, x_1, x_2, x_3, x_4 are the values of Equivdiameter and y_1, y_2, y_3, y_4 are the values of Circularity2. From experiments, the values were found to be $v_1 = 0.05, v_2 = 0.12, v_3 = 0.21, v_4 = 0.5, w_1 = 100, w_2 = 150, w_3 = 200, w_4 = 400, x_1 = 35, x_2 = 50, x_3 = 60, x_4 = 70, y_1 = 0.65, y_2 = 0.7, y_3 = 0.86$ and $y_4 = 0.9$

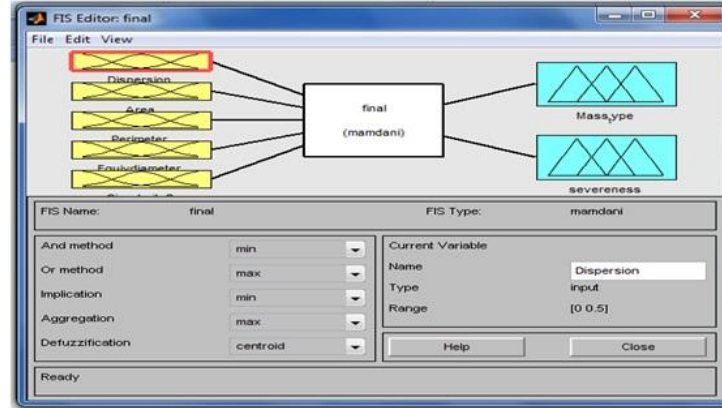


Fig.3 Fuzzy inference system using MATLAB.

RESULTS AND DISCUSSION

The images used for this work were collected from mammogram databases like mini MIAS and DDSM. The experiments were performed in MATLAB. For clearly defining the boundary between the masses and surroundings and for extracting the exact mass from the mammogram, gray threshold based approach is applied. Prior to segmentation, some pre-processing techniques like filtering and contrast enhancement are used. The performance measures used for selection of window size for the median filter are also discussed in this section. The results indicate that the fuzzy inference based classification of mammographic masses into Bi-RADS shape categories as well as benign or malignant works well on the dataset and the masses are classified effectively.

Performance Evaluation Metrics of Median Filter

To evaluate the performance of each window size of the median filter, performance measurement metrics such as Peak Signal to Noise Ratio and Mean Squared Error are used.

i) Peak Signal to Noise Ratio The Peak Signal to Noise Ratio (PSNR) between the filtered output image $y(i, j)$ and the original image $s(i, j)$ of dimensions $M1 \times M2$ pixels is defined as in equation. The higher the PSNR, the better the quality of the filtered image.

$$PSNR = 10 \log_{10} \left(\frac{R^2}{MSE} \right) \quad (2)$$

Where R is the maximum fluctuation in the input image data type and MSE is defined as

ii) Mean Squared Error The Mean Squared Error (MSE) is computed using the equation. The MSE represents the cumulative squared error between the filtered and the original image. The lower the value of MSE, the lower the error.

$$MSE = \frac{1}{M \times N} \sum_{M, N} [I_1(m, n) - I_2(m, n)]^2 \quad (3)$$

M and N are the number of rows and columns in the input images, respectively.

From the Table 1 it is observed that 3x3 window size outperforms other window sizes of the median filter.

Peak Signal to Noise Ratio (PSNR)					Mean Squared Error (MSE)				
Input images	Median (3x3)	Median (5x5)	Median (7x7)	Median (9x9)	Input images	Median (3x3)	Median (5x5)	Median (7x7)	Median (9x9)
Dataset 1	44.6748	40.1153	38.1465	36.7975	Dataset 1	2.2336	6.3819	10.0422	13.7004
Dataset 2	47.2145	40.7275	37.726	35.8618	Dataset 2	1.2446	5.5428	11.0633	16.9941
Dataset 3	39.0215	35.7881	34.6384	33.9693	Dataset 3	8.2098	17.2851	22.5239	26.2754
Dataset 4	38.6485	35.7414	34.8416	34.3572	Dataset 4	8.946	17.4719	21.4943	24.0306

Table 1 PSNR and MSE values of median filter for different window sizes

Classification accuracy

Classification accuracy is the most common evaluation method to measure the performance of the classifiers. Most researchers use it as the main parameter of criteria to evaluate the performance of their techniques. The higher the classification accuracy, the better the classifier is performing. The advantage of this measure lies in its simplicity; the disadvantage is that it can be deceptive (Brijesh Verma et al., 2010). In this paper, the classification accuracy was calculated by using the following formula:

$$\text{classification accuracy} = \frac{\text{correct classified patterns}}{\text{total number of patterns}} \quad (4)$$

The pre-processed and segmented images of dataset 1 (lobular shape), dataset 2 (oval shape), dataset 3 (round shape) and dataset 4 (irregular shape) are shown in Fig.4, Fig.5, Fig.6 and Fig.7 respectively. And the classification result is shown in the rule viewer of the fuzzy inference system which is shown in Fig.8. The classification accuracy for different shapes and severeness is presented in Table 2

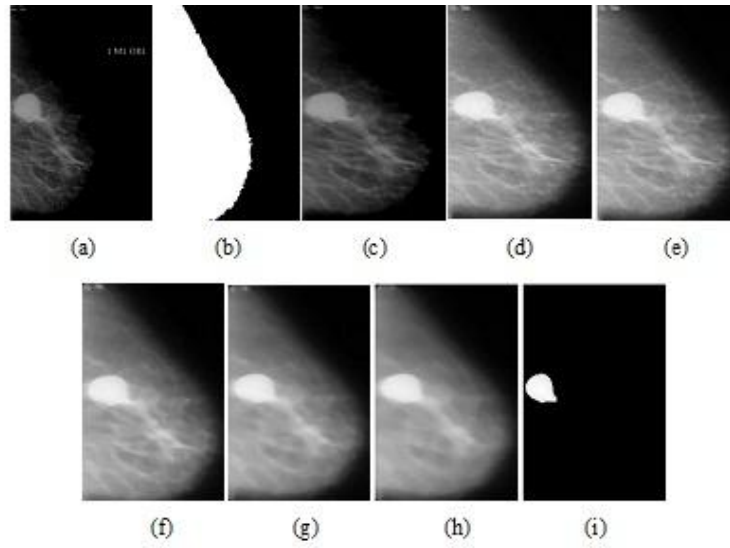


Fig.4 (a) Original (b) Binary (c) Cropped (d) Contrast enhanced (e) Median 3x3 (f) Median 5x5 (g) Median 7x7 (h) Median 9x9 (i) Segmented images of dataset 1.

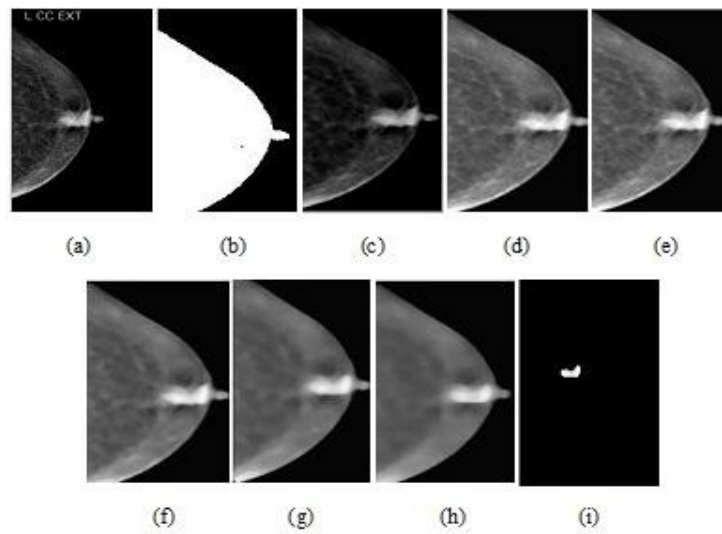


Fig.5 (a) Original (b) Binary (c) Cropped (d) Contrast enhanced (e) Median 3x3 (f) Median 5x5 (g) Median 7x7 (h) Median 9x9 (i) Segmented images of dataset 2.

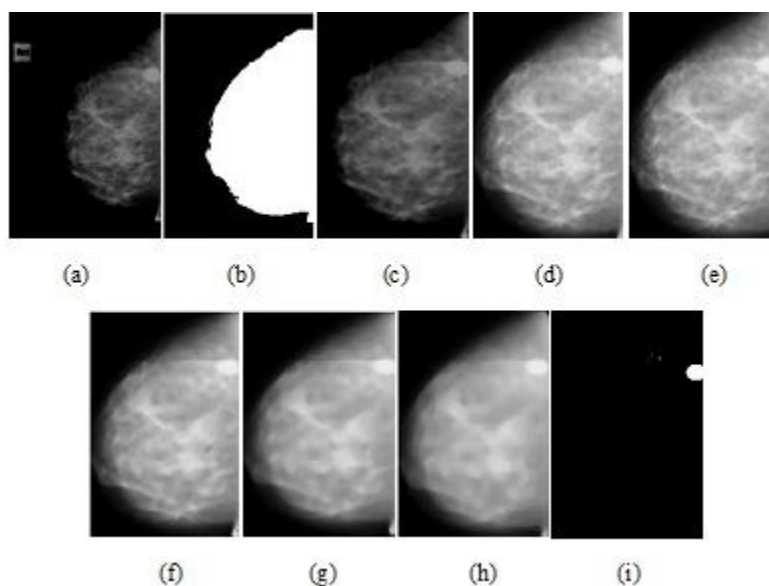


Fig.6 (a) Original (b) Binary (c) Cropped (d) Contrast enhanced (e) Median 3x3 (f) Median 5x5 (g) Median 7x7 (h) Median 9x9 (i) Segmented images of dataset 3.

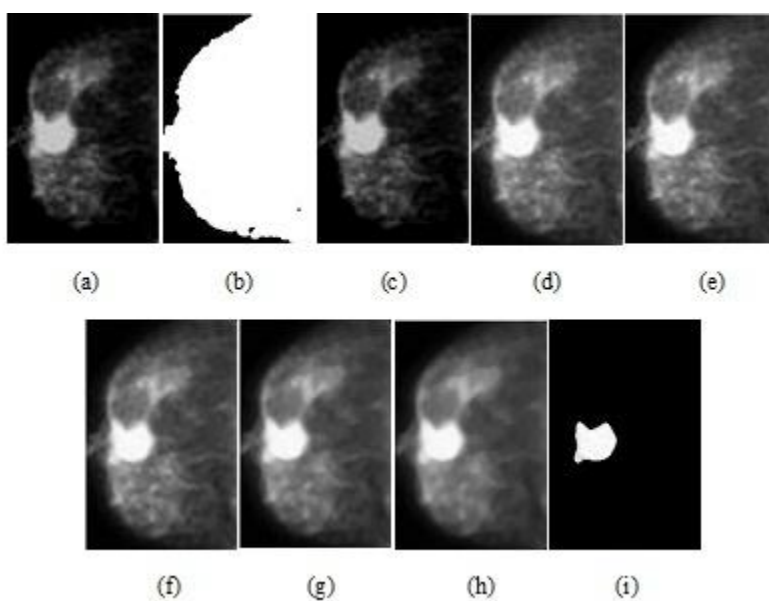


Fig.7 (a) Original (b) Binary (c) Cropped (d) Contrast enhanced (e) Median 3x3 (f) Median 5x5 (g) Median 7x7 (h) Median 9x9 (i) Segmented images of dataset 4.

Shape	Severeness	Total No. of images	Correctly classified	Classification accuracy (%)
Irregular	Malignant	30	28	93
Lobular	Malignant	20	17	85
Round	Benign	25	23	92
Oval	Benign	30	26	86
Lobular	Benign	20	18	90

Table 2 Classification accuracy

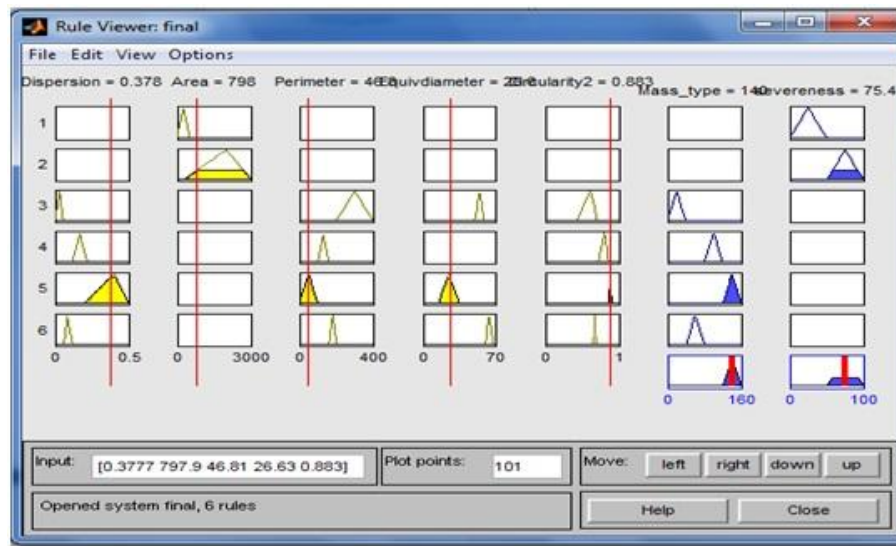


Fig.8 Rule viewer of FIS

CONCLUSION

As per the objective the mammographic masses were classified into BI-RADS shape categories and also as benign or malignant. The experimental results indicate that the fuzzy inference system that is constructed using MATLAB Fuzzy logic toolbox is easy and effective in classifying the mammographic masses. It is also found from the results that 3x3 window size is best suited for median filter used in denoising and Contrast Limited Adaptive Histogram Equalization (CLAHE) gives good contrast enhancement. Each identified mass in the mammogram is extracted and clearly the boundary is formed by using a gray level thresholding approach. It is found that the masses, which are represented using shape and margin properties, have certain amount of impreciseness. The persisting impreciseness is captured by fuzzy membership function and set of rules are also proposed for inference. Various set of rules are generated to recognize the masses either as round, oval, lobular, or irregular and benign or malignant. It is noticed that the performance of the proposed approach is encouraging.

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