A Fuzzy-Rule Based Algorithm for Contrast Enhancement of Mammograms Breast Masses *

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Abstract: Using fuzzy set theory, we present a fuzzy rule-based algorithm to perform contrast enhancement for digital mammography breast masses. Compared to the well-known histogram equalization enhancement technique, fuzzy rule-based enhancement is able to represent knowledge in a comprehensible way. Four measures of quantifying enhancement in digital mammograms have been introduced. Each measure is based on the statistical information obtained from the labeled region of interest and a border area surrounding it. The methodology is based on the assumption that target and background areas are accurately specified. To evaluate the performance of the algorithm, 25 images containing masses from the Mammographic Image Analysis Society (MIAS) database were selected.

Keywords: image enhancement; fuzzy set theory; fuzzy-rule-based image enhancement; contrast enhancement; Histogram equalization; breast cancer analysis

1. Introduction

Breast cancer is the type of cancer with highest incidence rates in women. It is the most common cause of cancer death in women in many countries, only exceeded by lung cancer in Asian countries and recently in the United States [4]. X-ray mammography is the most common technique used by radiologists in the screening and diagnosis of breast cancer in women. Although it is seen as the best examination technique for the early detection of breast cancer reducing mortality rates by up to 25%, their interpretation requires skill and experience by a trained radiologist [1,3]. Unfortunately, the main obstacle lays in low contrast between normal and malignant glandular tissues and the noise in such images that makes it very difficult to segment them. Therefore, in digital mammogram there is a need for enhancing imaging before a reasonable interpretation and segmentation can be achieved. Image enhancement in medical computing is the use of computers to make an image clearer which in return aid interpretation by humans or computers. Types of image enhancement include, noise reduction, edge enhancement and contrast enhancement [9]. In some X-ray mammogram radiographs, the features of interest occupy only a relatively narrow range of the gray scale. Contrast enhancement is a method to expand the contrast of features of interest so that they occupy a larger portion of the displayed gray level range without distortion to other features and the overall image quality. The goal of contrast enhancement techniques is to determine an optimal transformation function relating original gray level and the displayed intensity such that contrast between

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adjacent structures in an image is maximally portrayed [6]. A review of traditional contrast enhancement methods for digital radiography can be found in [1,2,4,7,10]. However, because mammograms have limited contrast it may be hard to see an anomaly. In this case, an enhanced image could both help the specialist to observe different structures in the image and to speed up checking each mammogram.

This paper presents fuzzy rule-based algorithm to enhance the contrast of mammogram images before segmentation process. The rest of this paper is organized as follows. Section (2) provides a brief discussion of the traditional image processing difficulties in mammogram analysis. Brief introduction on fuzzy image enhancement and the proposed fuzzy rule based enhancement algorithm are discussed in Section (3). Section (4) introduces the four quantitative measures. Results and conclusion are given in Section (5) and Section (6), respectively.

2. Mammograms Analysis Difficulties

Computerized schemes are being developed for the specific detection of either mass lesions or micro calcifications. This detection takes place in two steps. Firstly a pre-processing step is carried out in which the whole image is enhanced. Then the individual tumors are detected using different methods which include segmenting the tumors from the image and applying a specific mathematical method to accurately detect the position and size of the tumor [1]. The tumors detection in digital mammograms through traditional image processing is a difficult task due to the following reasons:

- Intensity levels vary greatly across different regions in a mammogram,
- Features for segmentation are hard to formulate,
- Subtle gray level variations across different parts of the image make the segmentation of tumor areas by gray level alone difficult,
- Tumors are not always obvious, especially where they are subtle or extremely subtle under the glandular tissues, which makes the task of interpretation difficult even for the radiologists themselves,
- Mammograms contain low signal to noise ratio (low contrast) and a complicated structured background,
- Breast tissue contrast and density vary with age, thus mammography produces varying image qualities, and
- Mammography images are not bimodal. As a result, any segmentation method, which utilizes an a priori or single threshold value method, is highly likely to generate serious segmentation errors.

3. Fuzzy Image Enhancement

The purpose of the image enhancement is to provide an automated tool to smoothing, deblurring, noise removing or, in the most case, gray level modification for an increase of contrast [10]. The gray level modification is one of the most popular methods to perform image enhancement because it is simple in implementation and fast in computing [8]. But the selection of suitable mathematical function for the gray level transformation depends on the specific grayness properties of the image, it is necessary to develop some techniques for automatic selection of an appropriate function. In recent years, many researchers have applied the fuzzy set theory to develop new techniques for contrast improvement [5,8,11,12,13,14] . It is based on gray level mapping into a fuzzy plane, using a membership transformation function. The aim is to generate image of higher contrast than the original image by giving a larger weight to the gray levels that are closer to the mean gray level of the image than to those that are farther from the mean.

An image *I* of size *M* x *N* and L gray levels can be considered as an array of fuzzy singletons, each having a value of membership denoting its degree of brightness relative to some brightness levels. For an image *I*, we can write in the notation of fuzzy sets:

$$I = \bigcup_{mn} \frac{\mu(\mathrm{g}_{\mathrm{mn}})}{g_{mn}} \qquad \mathrm{m} = 1,2,...,\mathrm{M} \ \text{ and } \ \mathrm{n} = 1,2,...,\mathrm{N} \tag{1}$$

Where g_{mn} is the intensity of (m, n)$^{\text{th}}$ pixel and μ_{mn} its membership value. The membership function characterizes a suitable property of image (e.g. edginess, darkness, textural property) and can be defined globally for the whole image or locally for its segments.

A fuzzy inference system is a rule-based system that uses fuzzy logic to reason about data [14]. Its basic structure consists of three main components, as depicted in Figure (1). The first component is the knowledge base, where the information required to make a fuzzy decision is stored. This includes the input membership functions, the rule list, and the output membership functions. The second component is the fuzzy inference kernel. A kernel consists of the core processes of a system. A single iteration of the fuzzy inference kernel will produce crisp outputs based on crisp inputs. The kernel applies the fuzzy inference process to the system in its current state. The third component of a fuzzy inference engine is the code that is responsible for gathering crisp inputs and actuating the required crisp outputs, and any scaling or other processing that may be required.

The decision-making process is performed by the inference engine using the rules contained in the rule base. These fuzzy rules define the connection between input and output fuzzy variables. A fuzzy rule has the form:

if antecedent then consequent,

Where antecedent is a fuzzy-logic expression composed of one or more simple fuzzy expressions connected by fuzzy operators, and consequent is an expression that assigns fuzzy values to the output variables. The inference engine evaluates all the rules in the rule base and combines the weighted consequents of all relevant rules into a single output fuzzy set.

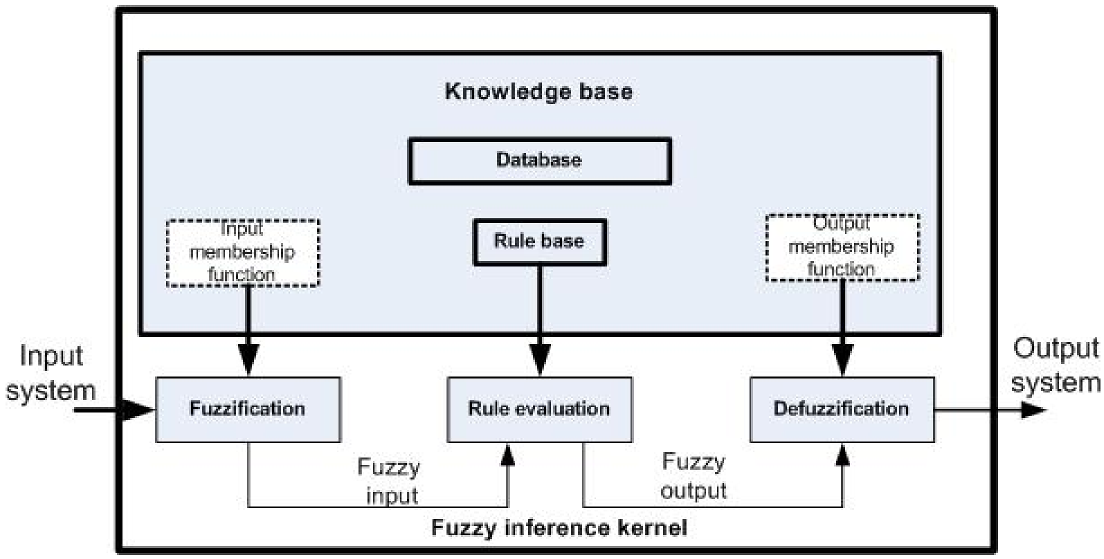

Fig. 1: The main principles of fuzzy inference system

3.1. Fuzzy rule-based contrast enhancement algorithm

Contrast enhancement is useful when an area of the image that is of particular importance has only subtle changes in pixel intensity. In these cases, it may be difficult for the human eye to make out the structures clearly, especially if the image is being displayed on a low quality screen. By exaggerating the changes in pixel intensity the image may become easier to interpret. Applying the contrast enhancement filter will improve the readability of areas with subtle changes in contrast but will also destroy areas of the image where the intensity of the pixels is outside the range of intensities being enhanced. The fuzzy rule-based approach is a powerful and universal method for many tasks in the image processing. In this paper a very simple inference rule-based system is adapted. Figure (2) depicts the fuzzification function.

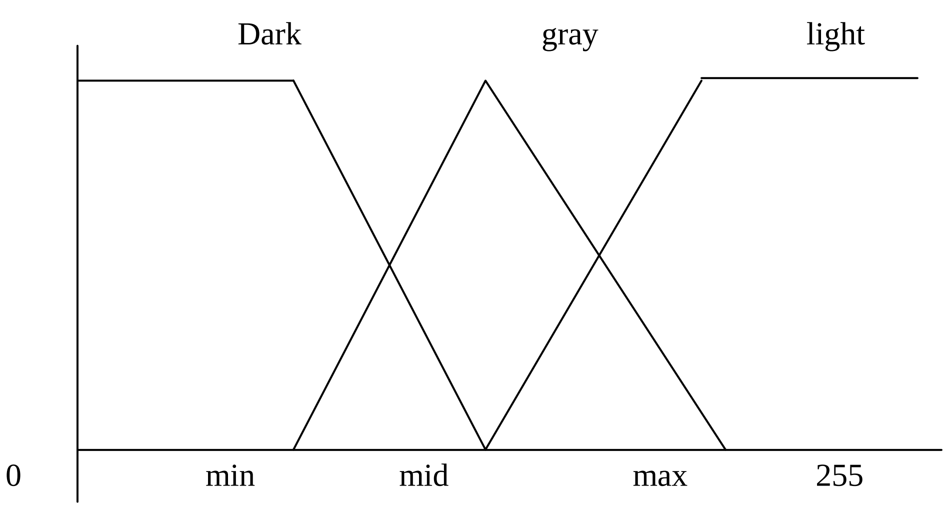

Fig. 2: Membership function

The algorithm consists of four phases. It starts by initialization the parameters of the image phase. Then by fuzzification of the gray levels phase (i.e., membership values to the dark, gray and bright) sets of gray levels. It followed by the grey level modification phase. Finally, defuzzification phase.

Phase 1: (Parameter initialization) The first phase of the algorithm is the initialization the parameters of image by finding the minimum (min) and maximum (max) grey levels. Then calculate the mid gray levels based on minimum and maximum grey levels.

Phase 2: (Fuzzification) The second phase of the algorithm is the fuzzification of the grey levels (i.e., membership values to the dark, grey and bright). Figure (3) illustrates the fuzzification procedure.

```
• For I=0; I<height; I++
• For J=0; J<width; J++
    o If 0<= data<=min then Fuzzydata_I=1;
        ▪ Else if min<=data<=mid Fuzzydata_I=(1/mid-min)*min-(1/mid min)*data;
    o If mid<= data<=max then
        ▪ Fuzzydata_I=(-1/max-mid)*mid+(1/max-mid)*data;
    o Else if max<=data<=255 then Fuzzydata_I=1;
    o If min<= data<=mid then
        ▪ Fuzzydata_II=(-1/mid-min)*min+(1/mid-min)*data;
    o Else if mid<=data<=max then
        ▪ Fuzzydata_II=(1/max-mid)*mid+1+(-1/max-mid)*data;
```

Fig. 3: Fuzzification procedure

Phase 3: (Grey level modification) The third phase of the algorithm is the inference procedure. Figure (4) illustrates the modification procedure.

```
• For I=0; I<height; I++
• For J=0; J<width; J++
    o If 0<= data<=min
        ▪ If dark THEN darker and set Fuzzydata_I=1;      //dark.
        ▪ Else if min<=data<=mid
    o For x=0; x<3; x++
        ▪ If 0<= Fuzzydata_I <=0 then
            • Fuzzydata_I=2*(Fuzzydata_I)^2;
        ▪ else if 0.5<= Fuzzydata_I <=1 then
            • Fuzzydata_I=1-2*(1-Fuzzydata_I)^2;
    o If mid<= data<=max        // light.
        ▪ For x=0; x<3; x++
        ▪ If 0<= Fuzzydata_I <=0.5 then
            • Fuzzydata_I=2*(Fuzzydata_I)^2;
        ▪ else if 0.5<= Fuzzydata_I <=1 then
            • Fuzzydata_I=1-2*(1-Fuzzydata_I)^2;
        ▪ Else if max<=data<=255
        ▪ IF light THEN lighter and set Fuzzydata_I=1;  / /gray.
        ▪ If min<= data<=mid then
            • Fuzzydata=min(Fuzzydata_I,Fuzzydata_II);
        ▪ Else if mid<=data<=max then
            • Fuzzydata=MAX(Fuzzydata_I,Fuzzydata_II);
```

Fig. 4: Modification procedure

<u>Phase 4: (Defuzzification)</u> Finally, defuzzification of the output using minimum (g_{min}), maximum (g_{max}) and medium (g_{mid}) of the gray levels such that the new enhanced gray level is computed by the following equation:

$$g = \frac{\mu_{dark} * g_{gray} + \mu_{gray} * g_{mid} + \mu_{bright} * g_{\max}}{\mu_{dark} + \mu_{gray} + \mu_{bright}} \qquad (2)$$

Figure (5) illustrates the defuzzification procedure.

- For I=0; I<height; I++
- For J=0; J<width; J++
  - If 0<= data<=min then
    - Enhanceddata=data; //Dark
  - Else if max<=data<=255 then
    - Enhanceddata=data; //light.
  - If min<= data<=mid //gray.
  - If Fuzzydata==Fuzzydata_II then
    - Enhanceddata=(mid-min)*Fuzzydata+min;
    - else Enhanceddata=-(mid-min)*Fuzzydata+min+(mid- min);
    - Else if mid<=data<=max
  - If Fuzzydata==Fuzzydata_II then
    - Enhanceddata=-(max-mid)*Fuzzydata+mid+(max-mid);
  - Else Enhanceddata=(max-mid)*Fuzzydata+mid;

Fig. 5: De-fuzzification procedure

4. Quantitative Measures

In this section we will introduce and describe four different quantitative measures [3] to evaluate the proposed algorithm.

A. Target to Background Contrast Measure based on Standard Deviation

A key object of a contrast enhancement is to maximize the difference between the background and target mean grey scale level and ensure that the homogeneity of the mass is increased aiding the visualization of its boundaries and location. Using the ratio of the standard deviation of the grey scales within the target before and after enhancement, we can quantify this improvement using the target to background contrast enactment based on the standard deviation. This measure is initially computed by determining the difference between ratios of the mean grey scales in the target and background images in the original and enhances images as:

$$TBC_{SD} = \left\{ \frac{(m_t^e / m_b^e) - (m_t^o / m_b^o)}{\sigma_t^e / \sigma_t^o} \right\} \qquad (3)$$

Where m_t^e, m_b^e, m_t^o and m_b^o are the mean of the grey scales comprising the target and background respectively of the original image before and after enhancement and where σ_t^e and σ_b^o the standard deviations of the grey scales are before and after enhancement.

Within the mammogram image, the target has a greater density within the mammogram thus having higher mean grey scale intensity compared to the surrounding background. A good enhancement algorithm should aim to enhance the contrast between target and background by increasing the mean grey scale of the target area and then reducing the mean grey of the background area, thereby increasing the value of TBC_{SD}.

B. Target to Background Contrast Measure Based on Entropy

The background contrast ratio can also be calculated using the entropy E of target and background areas within an image. This measure is computed in a similar manner to TBC_{SD} by determining the difference between ratios of the mean grey scales in the target and background areas in both original and enhanced images as:

$$TBC_{Entropy} = \left\{ \frac{(m_t^e / m_b^e) - (m_t^o / m_b^o)}{E_t^e / E_t^o} \right\} \tag{4}$$

Where E_t^e and E_t^o are the entropy of the target in the original and enhancement image, respectively. An effective enhancement algorithm will lead to a large value of $TBC_{Entropy}$.

C. Index of Fuzziness and Fuzzy Entropy

Index of fuzziness and fuzzy entropy are measures for global grayness ambiguity (fuzziness) of an image. They can be regarded as a degree of difficulty in deciding whether a pixel would be treated as black (dark) or white (bright). The index of fuzziness γ that gives the amount of fuzziness present in an image determines the amount of vagueness by measuring the distance between its fuzzy property plane and the nearest ordinary plane. Accordingly, entropy, H which makes use of Shanon's function, is regarded as a measure of quality of information in an image in the fuzzy domain. It gives the value of indefiniteness of an image. These quantities [Pal, S.K] are defined by the following equations:

$$\gamma = \frac{2}{MN} \sum_M \sum_N \min(\mu_{mn}, 1 - \mu_{mn}), \tag{5}$$

$$H = \frac{1}{MN \ln 2} \sum_M \sum_N - \mu_{mn} \ln(\mu_{mn}) - (1 - \mu_{mn}) \ln(1 - \mu_{mn}) \tag{6}$$

It should be noted that the decrease in the index of fuzziness and fuzzy entropy does not ensure proper enhancement of the images. We can only say that a good enhancement algorithm should reduce the grayness ambiguity. But, a low amount of ambiguity does not automatically lead to the desired enhancement effect.

5. Results

Figure (5) shows three experimental results of the proposed fuzzy-rule based enhancement algorithm compared with a histogram equalization result [15]. The first column shows the three different original images. Column two shows the histogram results. The third column shows the fuzzy enhancement results.

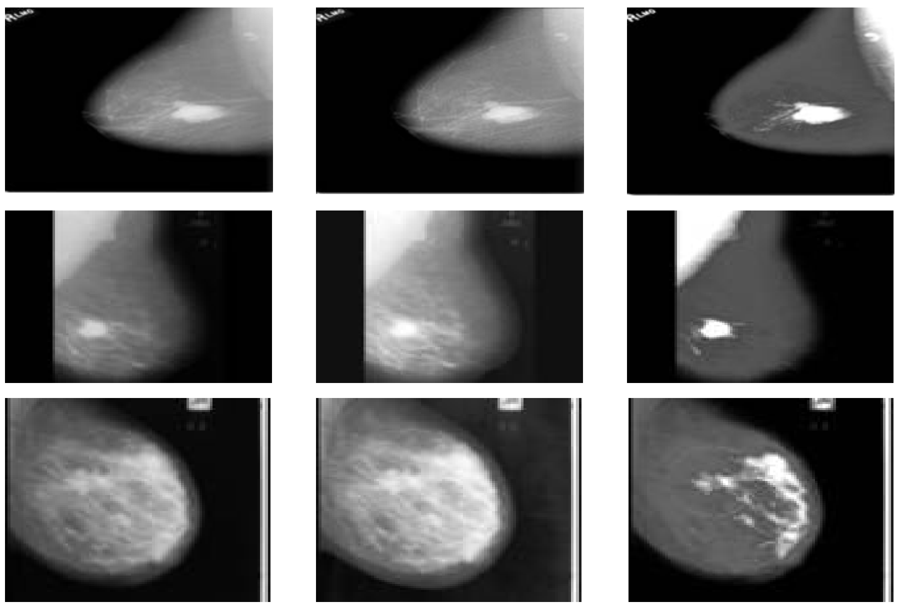

Fig. 5: Visual contrast enhancement results

Measures	TBC-SD		TBC-Entropy	
	Histogram	Fuzzy	Histogram	Fuzzy
Image1	0.01	0.47	0.011	0.92
Image2	0.61	0.92	-0.24	0.13
Image3	0.54	0.87	0.12	0.83

Table 1: TBC-SD and TBC-Entropy parameters for the enhancement results

	H		γ	
	Original	Fuzzy Enhanced	Original	Fuzzy Enhanced
Image1	0.289137	0.258460	0.217752	0.198138
Image2	0.0410322	0.0141429	0.00786895	0.0053892
Image3	0.453212	0.432536	0.286164	0.255001

Table 2: Grayness ambiguity

Form Table (1) we have to note that a good enhancement technique should aim to increase the contrast between target and background by increasing the ratio of mean grey in these areas. This background contrast ratio is calculated in a similar manner to the previous measure as the difference between the ratios of the mean grey in the target and background areas. An effective enhancement technique should aim to reduce the entropy of the target compared with the original. The final value of $TBC_{Entropy}$ will be larger for an effective enhancement technique. In addition the enhancement technique should aim to reduce the spread of grey scales in the enhanced target image compared with original. The final value of TBC_{SD} will be larger for an effective enhancement technique. Tables (2) demonstrate the grayness ambiguity. We observed that the index of fuzziness and the entropy decrease with enhancement.

6. Conclusion

A fuzzy based approach for enhancement of mammogram images is presented in this paper. The algorithm has been applied to a number of mammogram images and has shown good results. By evaluating the reliability of the measures using the fuzzy enhancement and histogram equalisation techniques, the results support the qualitative assessment of images that the fuzzy technique has a higher utility in the enhancement process.

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