A Novel Fuzzy Enhancement of Mammograms

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Abstract

Mammograms enhancement is very essential for detecting and diagnosing breast cancer at the early stage. In this paper, we propose a new enhancement method of mammograms based on intuitionistic fuzzy sets and type-2 fuzzy sets. Sugeno type intuitionistic fuzzy generator is used to construct a intuitionistic fuzzy set and a new membership function is defined using the Hamacher T co norm, and the final enhanced image is obtained using the arithmetic fusion operators. Experiments are performed on the cropped region of interest of real mammograms, and the comparison and evaluation of enhancement performance demonstrate that the proposed method improve the diagnostic efficiency by improving the contrast of the abnormal regions and fine details in mammograms.

1 Introduction

Breast cancer is the most common cancer among women worldwide. The American Cancer Society's estimates about 231,840 new cases of invasive breast cancer and about 40,290 deaths from breast cancer in women in the United States for 2015 [1]. Early detection of breast cancer is very important for reducing the mortality and prolong survival. Currently, mammograms (X-ray image) is the most common imaging technique to detect and diagnose breast cancer in the early stage [8]. However, mammograms are usually low contrast or low resolution due to the limitations of X-ray hardware systems, making it difficult for radiologists to diagnose and leading to more miss diagnosis. Therefore, a wide range of image enhancement methods have been proposed to improve the contrast and the visual quality of mammographic images. They can be categorized into two kinds of methods based on spatial-domain or transform-domain.

Spatial-domain methods: These methods are based on direct manipulation of intensity values in mammograms. Non-linear filters are desirable for mammograms enhancement as they well improve contrast and preserve edges and texture features. Adaptive density-weighted filter, tree-structured nonlinear filters, quadratic filters, morphological filtering are general non-linear filtering methods proposed for mammograms enhancement. Adaptive neighborhood (or region-based) contrast enhancement (ANCE) is another interesting technique that can be used to enhance mammograms as it's based on adaptive neighborhood and it can improve the contrast and features with varying shapes and sizes. Histogram equalization (HE) is an effective and well developed approach for mammograms contrast enhancement. However, HE always results in excessive contrast enhancement or washed-out effect because of changing the intensities globally. In order to overcome this drawback of HE, many other modified HE methods have been proposed, such as adaptive histogram equalization (AHE), contrast limited adaptive histogram equalization (CLARE), bi-histogram equalization (BHE), etc. Unsharp masking (UM) has a good performance to enhance the fine details of mammograms, but also with amplifying noise and overshooting steep details at same time. Rational UM (RUM) has been developed by replacing the high-pass filter of the traditional UM with a rational function operator. Nonlinear UM (NLUM) [7] proposed different types of filters into the nonlinear filtering operator so as to enhance fine details with no a *priori* knowledge of the image contents.

Transform-domain methods: These methods are developed by modifying transform coefficients of multi-scale subband representation of mammograms using the contourlet transform, discrete dyadic wavelet transform, or redundant discrete wavelet transform, etc. Mammographic images as well as other medical images contain lots of uncertainties and vagueness due to poor illumination and low contrast nature of these images. Since fuzzy sets theory is a suitable and effective tool to deal with the precision of classical mathematics [10] and the inherent precision of the real world, several fuzzy sets-based algorithms have been successfully used for mammograms enhancement [4]. Enhancement algorithms for mammograms using fuzzy sets theory first transform mammograms into fuzzy domain using means of a suitable membership function. Next, the membership plane is modified using non-linear operators. Finally, the enhanced mammograms can be obtained by defuzzification. But one of the main issues in interpreting mammograms by means of fuzzy sets is the selection of membership function which may be S-function or Gaussian or Gamma or any other. So there is a hesitation in the selection of membership function.

Atanassov's intuitionistic fuzzy sets (IFS) take account into hesitation degree in the form of membership function and more accord with the aspects of human decision-making. Type-2 fuzzy sets (T2FS) is another type of fuzzy sets proposed by Zadeh in 1975 [9] whose membership function are non-crisp. It is the new third-dimension of T2FS that make it model uncertainties more effectively than type-1 fuzzy sets. Therefore, T2FS have attracted much attention in many areas such as image processing, pattern recognition and decision making. However, there is very little work on mammograms enhancement using T2FS or IFS. Intuitionistic fuzzy enhancement on text documents was suggested by Kuppannan [5] where Contrast intensification (CI) operator on first and second type IFS is developed. Chaira [3] proposed a T2FS enhancement on medical image where they used Hamacher T co norm as an aggregation operator to form a new membership function.

In this paper, a novel image enhancement method using T2FS and IFS to increase the contrast of mammograms is proposed. Sugeno type intuitionistic fuzzy generator is used to construct the IFS and the hesitation degree is used to extend membership degrees to an interval established by upper and lower membership degrees. Hamacher T co norm is used as an aggregation operator to form a modified membership function. Experimental results demonstrate that the proposed method showed a better performance compared with several advanced mammograms enhancement methods.

The paper is organized as follows. Section 2 introduces the the preliminaries of IFS and T2FS. Section 3 introduces the proposed method in details. Experimental results and discussion are presented in Section 4 and conclusion is reached in section 5.

2 PRELIMINARIES

In this section the preliminaries of IFS and T2FS which are utilized throughout this paper are discussed.

2.1 IFS

Atanassov [2] have introduced the concept of IFS to reflect the fact that there may be some hesitation degree when assigns each pixel either to the background or to the object. An IFS A in a finite set X can be mathematically represented as Equation (1).

$$A = \{\langle x, \mu_A(x), v_A(x)\rangle | x \in X\} \tag{1}$$

where the function $\mu_A(x)$ and $v_A(x)$: $X \rightarrow [0,1]$ represent the membership degree and the nonmembership degree of an element x in a finite set X, respectively, with the necessary condition $0 \leq \mu_A(x) + v_A(x) \leq 1$. A new parameter $\pi_A(x)$ are taken into consideration due to the lack of knowledge or "personal error", which is called intuitionistic fuzzy index or hesitation degree. So an IFS A in X may be represented based on the hesitation degree as Equation (2).

$$A = \{\langle x, \mu_A(x), v_A(x), \pi_A(x)\rangle | x \in X\} \tag{2}$$

with the condition: $\mu_A(x) + v_A(x) + \pi_A(x) = 1$, $0 \leq \pi_A(x) \leq 1$.

2.2 T2FS

A type-2 fuzzy set T in X, is characterized by a type-2 membership function $\mu_T(x,u)$, can be mathematically symbolized as Equation (3) [6].

$$T = \{((x,u), \mu_T(x,u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \tag{3}$$

where $x \in X$ and $u \in J_x \subseteq [0,1]$, obviously $0 \leq \mu_T(x,u) \leq 1$. J_x and $\mu_T(x,u)$ are primary membership and secondary grade respectively.

When all $\mu_T(x,u) = 1$, then T is an interval T2FS (IT2FS), i.e the membership function of T for every element is not a single value but an interval. IT2FS can be written as Equation (4).

$$T = \{x, \mu_U(x), \mu_L(x) \mid x \in X\}, \mu_L(x) \leq \mu_T(x) \leq \mu_U(x) \tag{4}$$

Footprint of uncertainty (FOU) is a bounded region consist of all primary Memberships. Since the membership functions of IT2FS are interval membership functions, the FOU are uniform and can be characterized by the lower and upper of the membership functions, which in these paper are defined as Equation (5).

$$\mu_{upper} = \mu_A(x) + \pi_A(x), \mu_{lower} = \mu_A(x) + \pi_A(x) \tag{5}$$

where $\mu_A(x)$ and $\pi_A(x)$ are membership degree and hesitation degree in IFS, respectively.

3 METHODOLOGY

In this section the proposed method is described in details.

Step 1: Fuzzification.

The image (say A) of size $M \times N$ is initially fuzzified using the membership function as Equation (6).

$$\mu_A(x_{ij}) = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}} \tag{6}$$

where x_{ij} is the (i,j)th gray level of the image A ranges from 0 to L-1, L is the grayscale of the image A. $\mu_{A(x_{ij})}$ denotes the membership degree of the element x_{ij} in the image A . x_{min} and x_{max} are the minimum and maximum values of the gray levels of the image A. Hence, the image A in the fuzzy domain is defined by Equation (7).

$$F = \{x_{ij}, \mu_A(x_{ij}) \mid 0 \leq x_{ij} \leq L-1, 0 \leq \mu(x_{ij}) \leq 1\} \tag{7}$$

Step 2: Construction of IFS.

We construct IFS F_{IFS} using the Sugeno type intuitionistic fuzzy generator as Equation (8).

$$N(\mu(x_{ij})) = (1 - \mu(x_{ij})) / (1 + \lambda.\mu(x_{ij})), \lambda > 0 \tag{8}$$

where $N(1) = 0$, $N(0) = 1$. Taking into account the Sugeno type intuitionistic fuzzy generator, the nonmembership degree of the element x_{ij} in the image A donated can be written as Equation (9).

$$v_A(x_{ij}) = (1 - \mu(x_{ij})) / (1 + \lambda.\mu(x_{ij})) \tag{9}$$

F_{IFS} can be mathematically symbolized as Equation (10).

$$F_{IFS} = \left\{\left(x_{ij}, \mu_A(x_{ij}), \frac{1 - \mu_A(x_{ij})}{1 + \lambda.\mu_A(x_{ij})} \mid x \in A\right)\right\} \tag{10}$$

The hesitation degree of the element x_{ij} in the image A (from Eq.(2)) is written as Equation (11).

$$\pi_A(x_{ij}) = 1 - \mu_A(x_{ij}) - \frac{1 - \mu_A(x_{ij})}{1 + \lambda.\mu_A(x_{ij})} \tag{11}$$

where the condition $\mu_{A}(x_{ij}) + \nu_A(x_{ij}) + \pi_A(x_{ij}) = 1$ holds. Due to the hesitation in the membership function, the new membership values $\mu_T(x_{ij})$ lie in the interval range as Equation (12).

$$\mu_T(x_{ij}) = [\mu_A(x_{ij}) - \pi_A(x_{ij}), \mu_A(x_{ij}) + \pi_A(x_{ij})] \tag{12}$$

Step 3: Construction of IT2FS.

Construct the IT2FS F_{IT2FS} using the upper and lower ranges of the interval $\mu_T(x_{ij})$ as Equation (13).

$$\mu_{\text{upper}} = (\mu_A(x) + \pi_A(x))^{\alpha}, \mu_{lower} = (\mu_A(x) - \pi_A(x))^{\alpha} \tag{13}$$

where α is a parameter to adjust the upper and lower ranges of the IT2FS membership function with the condition α>0, and α is determined experimentally in this paper.

Step 4: Hyperbolization.

The modified membership function are computed using the Hamacher T co norm as Equation (14).

$$\mu_{\text{enh}} = \frac{\mu_{upper} + \mu_{lower} + (m-2)\mu_{upper} \cdot \mu_{lower}}{1-(1-m)\mu_{upper} \cdot \mu_{lower}} \tag{14}$$

where μ_{enh} is the new membership function of the enhanced image, and m is the average of the image. Then Convert μ_{enh} into the pixel plane as as Equation (15) .

$$x_{ijenh} = \mu_{\text{enh}} \cdot (x_{\max} - x_{\min}) + x_{\min} \tag{15}$$

where x_{ijenh} is the new gray level of the (i,j) pixel of the image A.

Step 5: Fusion.

The final enhanced image is obtained using the arithmetic fusion processes as Equation (16).

$$E(i,j) = A_1 x_{ij} + A_2 \frac{x_{ijenh}}{|x_{ijenh}|_{\max}} . x_{ij} \tag{16}$$

where A_1 and A_2 are the scaling factors and $|x_{ijenh}|_{\max}$ is the maximum absolute value of new gray level x_{ijenh}.

4 RESULTS AND DISCUSSION

In this section, we present some of the experimental results of 20 real mammograms obtained using the proposed method and we compare the results of the proposed method with RUM, NLUM, direct image contrast enhancement (DICE). Since some characteristic lesions like microcalcifications, masses and abnormal regions are very essential indicator of breast cancer, all test mammograms are cropped into images with smaller sizes for analysis such that the cropped ROIs contain most of characteristic lesions that may be useful to detect and diagnose breast cancers. In the experiment, λ = 1 is used, the parameters of α , A_1 , A_2 used for the proposed enhancement were decided by a subjective test and the value of which can get the best visual quality were selected.

Fig. 1 shows cropped ROIs of three original mammograms with different characteristics of microcalcifications or masses, and the enhanced results by the proposed method and three advanced methods. They clearly show that the proposed is capable of improving the contrast of abnormal regions and preserving fine details in mammograms. Figs. 1 (a5)~(c5) shows that the our method is good at improving the visual quality and the fine details of the cropped ROIs. The distribution of microcalcifications and masses of the proposed is more clear than NLUM, RUM, DICE, as shown in Figs. 1 (b2)~(b5) and (c2)~(c5), respectively. The DICE slightly improves the contrast of abnormal regions, but it generates obvious artifacts, as shown in Fig. 1 (a2)~(c2). The RUM has very limited contrast improvement and produces many spot artifacts, as shown in Fig. 1 (a3). The NLUM improve the contrast and visual quality of the mass regions, but the enhanced images are darker and the microcalcifications are not visible properly, as shown in Figs. 1 (a4)~(c4).

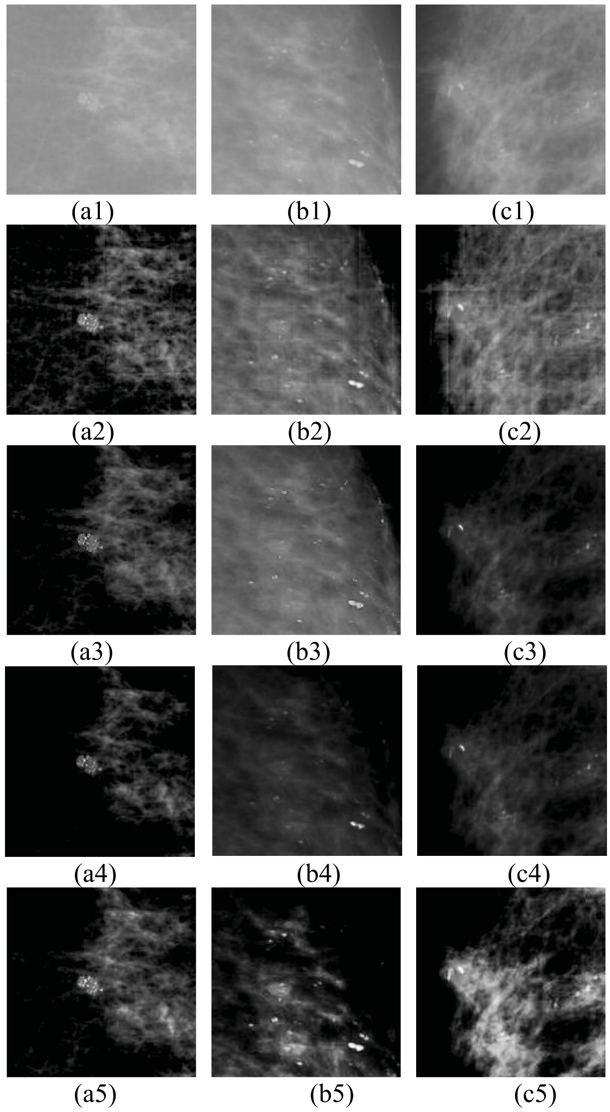

Figure 1: Comparison of mammogram enhancement using different algorithms. (a1) Cropped ROIs contain masses, (b1)~(c1) Cropped ROIs contain microcalcifications. (a2)~(c2) Enhanced results of (a1)~(c1) by using the DICE. (a3)~(c3) Enhanced results of (a1)~(c1) by using the RUM. (a4)~(c4) Enhanced results of (a1)~(c1) by using the NLUM. (a5)~(c5) Enhanced results of (a1)~(c1) by the using the proposed method.

Fig. 2 are the cropped ROIs with dense breast and abnormal regions for analysis. As shown in Figs. 2 (a5)~(c5), the shape of the dense regions of the proposed method is very clear and easily discernable, and the fine details are also distinctly improved. As evident from Figs. 2 (a2)~(c2), the DICE generates obvious "block artifacts". The contrast and visual equality of the enhanced images using the RUM and NLUM are slightly improved and are difficult to improve the diagnostic efficiency for radiologists, as shown in Figs. 2 (a3)~(c3) and (a4)~(c4).

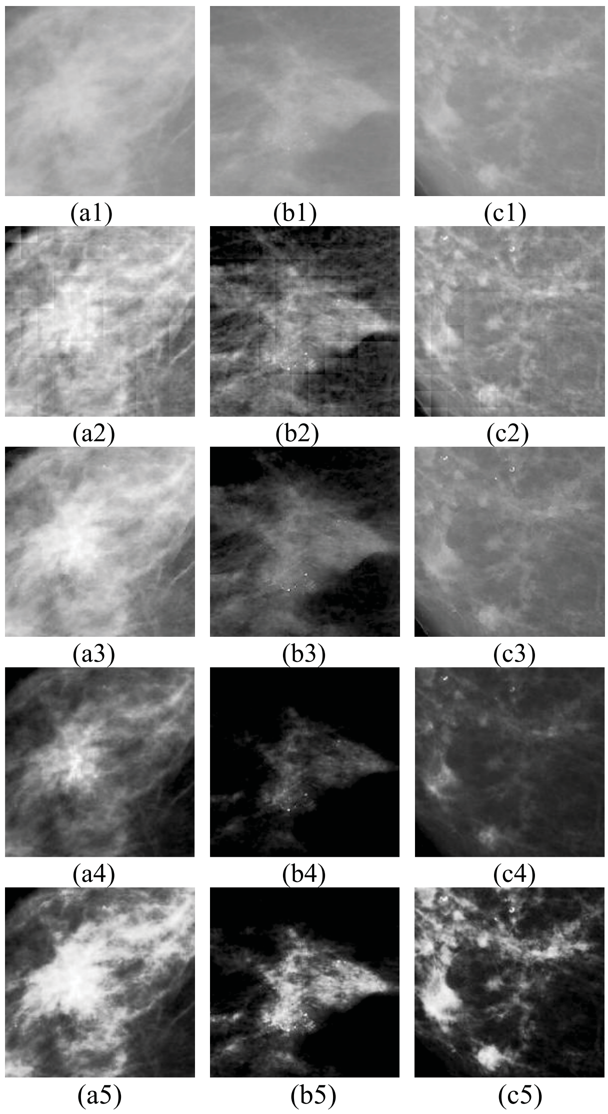

Figure 2: Comparison of mammogram enhancement using different algorithms. (a1)~(a3) Cropped ROIs contain dense breast and abnormal regions. (a2)~(c2) Enhanced results of (a1)~(c1) by using the DICE. (a3)~(c3) Enhanced results of (a1)~(c1) by using the RUM. (a4)~(c4) Enhanced results of (a1)~(c1) by using the NLUM. (a5)~(c5) Enhanced results of (a1)~(c1) by using the proposed method.

A region contrast C_w based on Laplacian operator is calculated to evaluate the performance of the proposed method quantitatively. The definition of C_w in image I can be written as Equation (17).

$$C_W(I) = \frac{1}{m}\sum_{w} |c(x,y)| \log(1 + |c(x,y)|) \tag{17}$$

Where $c(x,y)$ is the local contrast at pixel (x,y), is defined as Equation (18).

$$c(x,y) = 4I(x,y) - \{I(x-1,y) + I(x,y-1) + I(x+1,y) + I(x,y+1)\} \tag{18}$$

where $I(x,y)$ is the $(x,y)th$ intensity value of the image I, w is a region of image I, and m is the number of the pixel in the region w. Table 1 shows the measure results of the enhanced images using C_w. It is observed that the proposed enhanced images have higher average contrast value implies that the images are enhanced in a better way. The measure results verify the enhancement performance of the proposed method outperforms the others in quantitative.

	Original	DICE	RUM	NLUM	Proposed
1	1.3848	9.0195	6.4050	5.5088	10.5059
2	1.1863	11.2190	8.6145	5.7284	12.2766
3	2.4476	6.9407	8.0606	3.3972	9.0704
4	1.8592	6.3638	5.5354	1.7506	6.7276
5	2.0093	10.4505	7.4687	3.8696	11.3592
Ave.	1.7774	8.7987	7.2168	4.0509	9.9879

Table 1: Region contrast of the original mammograms and the enhanced mammograms by different algorithms.

5 CONCLUSIONS

This paper has introduced a novel enhancement method based on T2FS and IFS for mammograms. Sugeno type intuitionistic fuzzy generator is used to construct a IFS and a new membership function is defined using the Hamacher T co norm, and the final enhanced image is obtained using the arithmetic fusion operators. The simulation results have demonstrated that the proposed method shows better performance for improving the contrast of abnormal regions, visual quality, fine details in mammograms compared with he results of the conventional enhancement method. Our method is also useful for detecting and diagnosing diseases or breast cancer at the early stage.

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