TOWARD A NEURO-FUZZY SYSTEM FOR MAMMOGRAM ENHANCEMENT

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Abstract— Breast cancer continues to be a significant public health problem in Brazil. Approximately 8 000 women die of breast cancer each year. Even more disturbing is the fact that many diagnosis are only realized when the cancer is in advanced stage. However, mammograms are still being considered an important tool for diagnosis. This paper presents a neuro-fuzzy system for enhancement of mammogram based on a committee machine composed by a bank of filters. In the actual stage of the project, a fuzzy filter was developed presenting encouraging results. This systems can be used alone or in a more complete system, for automatic identification and diagnosis, as a pre-processor module.

Key Words— fuzzy systems, neural networks, digital image processing

1 Introduction

Results of recent researches show that the previous detection of breast cancer increase the survival chance. Currently, the rate cost/benefit shows that mammography is the best detection method available, however, its superiority has some limitations. The image quality must be such that the minimum difference in radiological density of the several tissues would be reproduced with the maximal possible contrast. However amount of X-Rays used must be small, as it can cause development or acceleration of the cancer cells. This fact contributes to small quality of contrast and sharpness of the mammograms.

Due to image quality with small contrast and small differentiation between the parts that constitute the mama, there is a necessity to the professional to carry out a visual effort for image interpretation. Moreover, there is the problem of individual perception ability. Each person looks at an object with a different perception.

The exact causes of breast cancer are still unknown and the mammogram is a hard image to interpret, thus its necessary to the examiner to have a large experience to avoid mistakes. To help the medical doctors in the analysis and diagnosis of medical images, automatic systems for diagnosis support has been an important research field due to the large amount of data to be analyzed in a short period of time (Economou et al., 1996).

In this work, we propose a neuro-fuzzy system with a committee machine architecture. In this system a neural network combines the results of several individual filters to improve the sharpness of the mammogram and also enhance the lesions areas.

This systems is still in the development. In the current stage we developed a fuzzy filter able to improve the sharpness and to enhance mammograms using a rule base generated from local expertise knowledge that synthetize a group of commom operations used in mathematical morphology. The results obtained were encouraging.

2 Background

With the objective of improving medical images quality, several researches have been carried out using different techniques such as wavelets (Unser and Aldroubi, 1996)-(Alaylioglu and Aghdasi, 1998), neural networks and fuzzy systems (Hojjatoleslami et al., 1997)-(Verma, 1998).

Brzakovic et al. (1990) developed a system for automatic detection and classification of tumors in mammograms where the analysis was performed in two stages. First, the system identified a group of pixels that could correspond to a tumor. Then, the group was submitted to classification. The essence of the first stage was the multiresolution image processing based on fuzzy pyramid linking. In the second stage a hierarchical classification was applied to identify maligns and benign tumors.

Woods et al. (1992) developed a dynamic supervised neural network to detect microcalcifications in mammograms. A segmentation process was used to extract candidates objects from the mammograms and a neural network determined if the objects were really microcalcifications.

Zarndy et al. (1994) developed two algorithms based in cellular neural networks. The first found and restored microcalcifications; the second found small lesions around the tumor.

B. Zheng et al. (1996) proposed a mixed feature based neural network (MFNN) for clusters microcalcifications detection in mammograms. The MFNN used characteristics obtained from spatial and spectral processing along with spectral entropy as the decision parameter.

Cheng et al. (1998) presented a new approach to microcalcification detection based on fuzzy systems. The microcalcifications were enhanced based on brightness and non-uniformity and the irrelevant details were excluded. The essential idea of this approach was to combine the enhanced image by the fuzzy filter with the original image to preserve fidelity.

Theses works presented encouraging results in the image enhancement and illness classification. However, in general, they failed to present interest on improving image sharpness, which is very useful because it turns the human and computer based analysis easier. The sharpness permits a better overview with detail richness. This can be very useful in surgery cases. Our proposed system aims to overcome these limitations in the mammograms cases.

3 The Neuro-fuzzy System

Combination of fuzzy and neural paradigms is getting an increasing importance in the development of non-linear filters due to their learning abilities. Following this tendency, we propose through this work a neuro-fuzzy architecture composed of several filters accomplishing different tasks and acting simultaneously over an image. A neural network is trained to decide, from the individual results of each filter, which should be the final result. Thus, we compose a committee machine as presented in the Figure 1.

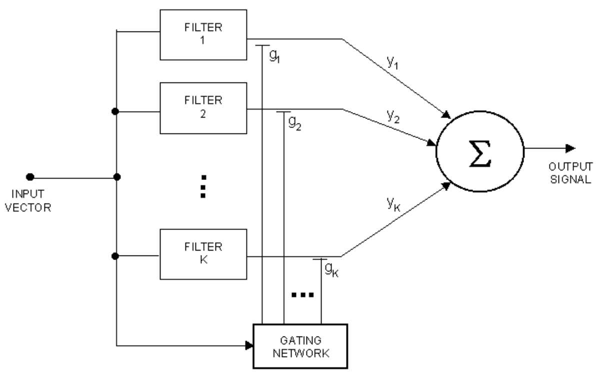

Figure 1. Neuro-fuzzy System for mammogram enhancement

Specifically, this system consists of K supervised modules called filters and an integration unit called gating network that performs the function of mediator of the several filters. We consider that the filters are specialized to work in different regions of the input space. Thus, the output S is given by:

$$S = G^T Y \tag{1}$$

$$G^T = [g_1, g_2, \ldots, g_K] \tag{2}$$

$$Y^T = [y_1, y_2; \ldots, y_K] \tag{3}$$

where G is a weight vector, Y is a vector composed by the output of the individual filters and K is the number of filters that compose the committee machine.

The gating network consists of a unique layer of K neurons, where each neuron is associated to a specific filter (Haykin, 1999). The gating network neurons are non-linear and have activation function defined by:

$$g_k = \frac{exp(u_k)}{\sum_{j=1}^{K} exp(u_j)} \ , \quad k = 1,\ 2,\ \ldots, K \tag{4}$$

where u_k is the inner product of the input vector X by the synaptic wight vector a_K:

$$u_k = a_k^T X \ , \quad k = 1,\ 2,\ \ldots,\ K \tag{5}$$

3.1 The Fuzzy Filter

The fuzzy filter developed in this work utilizes structure of a fuzzy logic system (FLS) defined by Mendel (Mendel, 1995) which is shown in the Figure 2. A FLS has four basic components: the rule base, the fuzzifier, the inference engine and the defuzzifier. After defining the rules, a FLS can be considered as a mapper from the input space to the output space.

The input image is the original mammogram and the output image is the filtered mammogram which is sharper and have lesion areas enhanced. The input vector generator module utilizes a sliding window spatial filter to generate the inputs to the fuzzy filters. Thus, the inputs are the gray levels differences between the central pixel of the sliding window and its 8-neighbors in the input image.

Let $x(n)$ be the pixel located in position $n = [n_1, n_2]$ in the input image and $y(n)$ the corresponding pixel in the output image, then:

$$0 \le x(n) \le L-1 \ , \ 0 \le y(n) \le L-1 \tag{6}$$

Moreover, let $H = \{x_0, x_1, x_2, \ \ldots \ , x_8\}$ be the set of pixels that belong to a window of size 3×3 centered in $x(n)$, where $x_0 = x(n)$. Thus, the filter inputs are defined by:

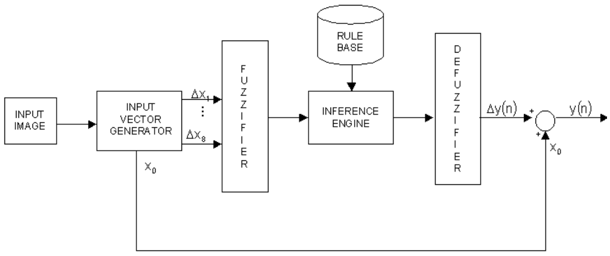

Figure 2. Block diagram of the fuzzy filter

$$\Delta x_i = x_i - x_0 \quad , \; i = 1, 2, 3, \; \ldots \; 8 \tag{7}$$

This filter has a rule base that is presented in section 3.2, with first type-Larsen's inference engine, singleton fuzzifier, center average defuzzifier and gaussian membership functions defined by:

$$\Delta y(n) = \frac{\sum_{l=1}^{M} C^l \left[\prod_{k=1}^{8} \mu(\Delta x_k)\right]}{\sum_{l=1}^{M} \left[\prod_{k=1}^{8} \mu(\Delta x_k)\right]} \tag{8}$$

where M is the number of fired rules for a given input vector ΔX, l is the index which indicates fired rules order and k is the index that indicates the input vector elements order ΔX.

The membership functions of the fuzzy sets of the input and output variables are shown in the Figure 3 and are defined by:

$$\mu_p(\Delta x) = 1 - \frac{2|\Delta x - a_p|}{b_p} \tag{9}$$

Where: a_p is the center of the fuzzy set p and b_p is its aperture.

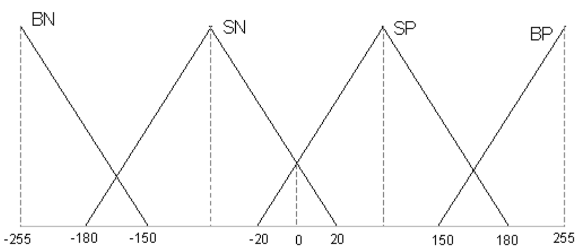

Figure 3. Membership functions of the input and output fuzzy sets (BN - big negative, SN - small negative, SP - small positive and BP - big positive)

Thus, the output filter $y(n)$ is given by:

$$y(n) = x(n) + \Delta y(n) \tag{10}$$

Where: $-L + 1 \leq \Delta x_i \leq L + 1 \quad , \quad -L + 1 \leq \Delta y_n \leq L + 1$

3.2 Rule Base

One of the main advantages of the fuzzy systems is its capability of incorporating expertise knowledge through fuzzy rules. Observing the displacement of a window though several regions of the input image, we can discover rules which determine the action to be taken when it goes through theses regions. This rules acquirement mechanism was studied in other works (Russo and Ramponi, 1995)-(Russo, 1999).

Dilation and erosion are two operations that define the mathematical morphology algebra. The dilatation process consists of obtaining the reflection of B (denoted $\hat{B}$) about to its origin and then shifting this reflection by x. The dilatation of A by B then is the set of all x displacements such that $\hat{B}$ and A overlap by at least one nonzero element. The set B is commonly referred as structuring element (Gonzalez and Woods, 1992).

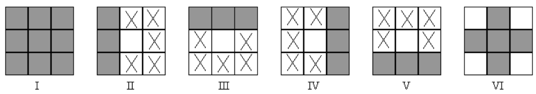

Figure 4. Structuring Elements

The basic idea is to probe an image with a structuring element and quantify the manner in which the structuring element fits (or does not fit) within the image. The structuring element is shifted through the image. In some locations it fits, in others locations it does not fit. By marking the locations at which the structuring element fits within the image, we derive structural information concerning the image (Dougherty, 1992). The choice of the appropriated structuring element is determined basically by the kind of information desired.

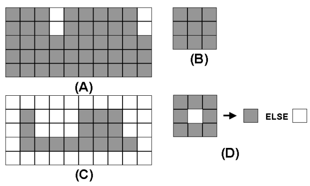

Figure 5. (A) Set A (image), (B) Set B (structuring element), (C) Erosion of the set A by the set B, (D) Rule for erosion

Observing the mathematical morphology algorithms, we realized that it was possible to create rules which perform several morphological operations simultaneously, and could be applied to mammogram and thus offer as output, sharper mammograms with enhanced lesions.

As an exemple we can see in Figure 5(C) the erosion of the set in Figure 5(A) by the structuring element in Figure 5(B), and Figure 5(D) is a rule that also can perform the erosion over the set A and can lead to the same result. Thus, we developed a group of ten rules shown in Figure

6, based on the structuring elements presented in the Figure 4.

Formally, theses rules are expressed in following form:

IF (Δx_1,SN) AND (Δx_2,SN) AND (Δx_3,SN) AND (Δx_4,SN) AND (Δx_5,SN) AND (Δx_6,SN) AND (Δx_7,SN) AND (Δx_8,SN) THEN (Δy,SP)

IF (Δx_1,SP) AND (Δx_2,SP) AND (Δx_3,SP) AND (Δx_4,SP) AND (Δx_5,SP) AND (Δx_6,SP) AND (Δx_7,SP) AND (Δx_8,SP) THEN (Δy,SN)

$\vdots$

IF (Δx_1,SN) AND (Δx_2,SP) AND (Δx_3,SP) AND (Δx_4,SN) AND (Δx_5,SP) AND (Δx_6,SN) AND (Δx_7,SP) AND (Δx_8,SP) THEN (Δy,SN)

These rules have the objective of performing several mathematical operations with different structuring elements simultaneously and weighted by the equation 8, resulting in a output image with enhanced and sharper lesion areas.

The Figure 6 is a graphical representation of the above presented rules. The group of squares on the left of each arrow represents the consequent of each rule and the single square on the right of each arrow represents the consequent of each rule and the arrow indicates implication relation. The white squares correspond to the fuzzy set SN (Small Negative) and the gray squares correspond to the fuzzy set SP (Small Positive).

These rules can be better understood though the analysis of their results when they are applied either to uniform regions or to edges regions.

In the first case, the local differences that constitute each input assume small values. Due to the superposition of the fuzzy sets SN and SP, the rules are fired with approximately the same confidence degree, and thus the final effect is a small correction term $\Delta y(n)$, generating a small or null enhancement in uniform regions.

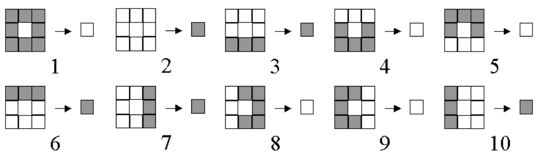

Figure 6. Rule base for mammogram enhancement

In the second case, the presence of a gap of difference in the window generates local large differences that constitute the input variable. These values are out of the superposition region, thus the rules are fired with different confidence degree and then some of them act with intensity greater then others that could be eventually inactive. The rules action generates a correction value $\Delta y(n)$, opposite to the gray level variation of the pixels of the window that goes through the input image, causing an improvement of contrast. Applying the filter successively to an image, several regions are gradually enhanced.

3.3 Filter Results Analysis

In diagnosis, mammography analysis yields one of the following classes: 1) radiologically normal, 2) benign lesion, 3) probable benign lesion, 4) suspect malign lesion and 5) highly suspect malign lesion.

If a patient presents characteristics of class three, she should be submitted to a status mama monitoring through new mammography or ultrasonography. To patients of the classes four and five, biopsies are suggested. The frontier between classes three and four are, in general, conditioned to subjective interpretation, based on the mammograms that sometimes are blurred and have small sharpness.

The proposed filter was applied successively to mammmograms. In each filter, interaction of only 25% of the value $\Delta y(n)$ was added to the output image, in other words, $y(n) = x(n) + 0.25\Delta y(n)$. Through this procedure we obtained a sequence of filtered images. The first images presented an increase sharpness that resulted, in the final images, to enhanced lesions areas as shown in the Figure 8.

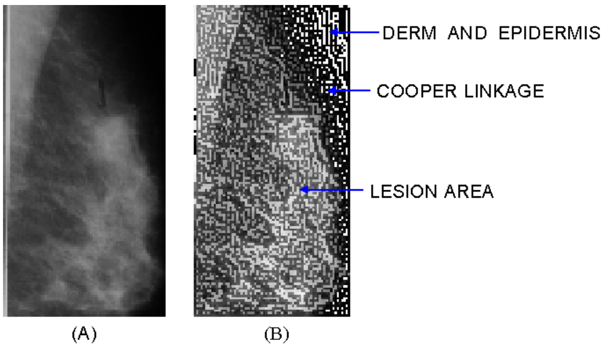

Figure 7. (A) Original mammogram (B) Enhanced mammogram

We can observe that while enhancement become stronger the images have a lost of sharpness. On the other hand we can observe that the finals enhanced images make visible several tissue that have different radiological density. As an example we can see in Figure 7(A) the original mammogram and in Figure 7(B) mammogram enhanced after five interactions of the proposed filter. Comparing these images we observe that the proposed filter makes visible details that invisible in the original image such as derm , epiderm and Cooper linkage and it also enhance lesions areas. Thus the proposed filter provides images richer then those provided by IAM system and that are useful in surgery cases since it offer information that are not visually detected in the original mammograms.

In Figure 9 (a) is the original blurred image, in (b) is the result of the first application, (c) is the result of the third application and (d) the image enhanced by the IAM system (Anguh and Silva, 1997).

Comparing the results obtained with those of IAM, we can observe in Figures 9(c) and 9(d) that the lesion areas enhanced by the proposed filter coincide with those enhanced by the system IAM. These are the areas that have a greater radiological density which characterizes lesions and would need a deeper analysis.

From the presented results, we can verify that despite the fact that the proposed filter did not define the images with high precision and colors as the IAM does, it offer sharper and enhanced images that allows the professional to see small details and fine lines that would be useful in surgery cases.

To improve further the finals results of the committee machine, we suggest an inclusion of an edge extraction filter for a better definition of the lesion areas in the final filtered image.

We believe that with the images obtained by the fuzzy filter and the ones obtained by the system IAM we provide to the professionals different images of the same situation that emphasizes different aspects of the mammogram. Thus, they will have more information to help them in diagnosis.

4 Conclusion

From local expertise knowledge, it is possible to obtain a rule base for fuzzy filter which is able to filter blurred mammograms and offer final filtered mammograms sharper along with enhanced lesion areas.

These rules are equivalent to a group of morphological operations with several different structuring elements applied simultaneously and weighted by the developed fuzzy filter.

Using the proposed filter and another dedicated to edge detection, or other relevant tasks, we can compose an neuro-fuzzy system with a committee machine architecture and then we expect to obtain results that will combine the relevant characteristics of each filter to generate better final images.

A committee machine system like that would probably be used in a pre-processing module of more advanced system for automatic diagnosis in mammography.

Thus, with this proposed fuzzy filter, and the improvements that are currently been studied, we wish to obtain a system able to offer to medical doctors images that could serve as support to analysis and diagnosis in breast cancer cases.

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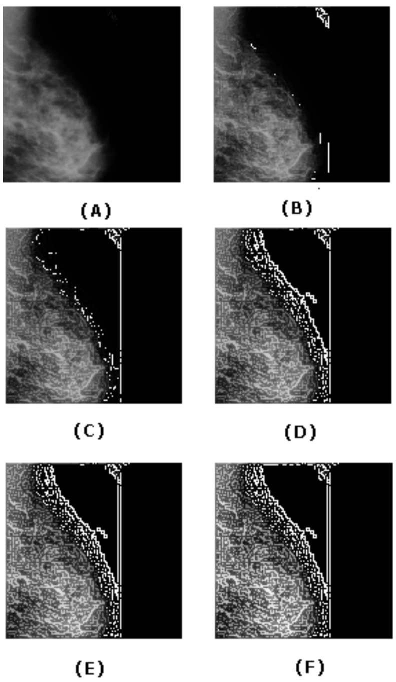

Figure 8. Successive filtering results: (A) original image, (B) first interaction, (C) second interaction, (D) third interaction, (E) fourth interaction e (F) filfth interaction

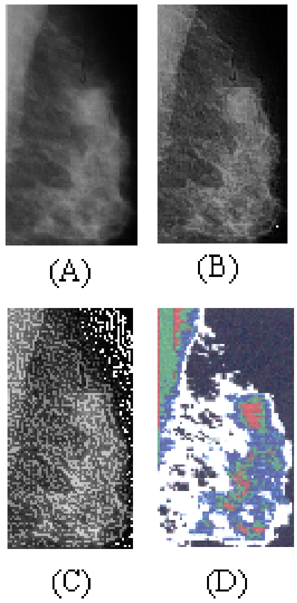

Figure 9. Comparison of results: (A) original image, (B) resulting image after two interactions, (C) resulting image after five interactions and (D) enhanced image by IAM system