Contrast enhancement of mammographic images by digital images processing

Mejora de contraste de imágenes de mamografía mediante procesamiento digital de imagen

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Abstract

This paper shows the obtained results of applying image enhancement techniques in regions of interest extracted of mamographies. The objective is to improve the detection of breast lesions, such as the microcalcifications and thus contribute to the early detection of breast cancer. Usually, the quality of the region of interest images is not better, and they have some deficiencies that difficult the microcalcifications detection. Due to this, the approach in this paper is to increase the quality of the region of interest image by means of edge and contour enhancement, modifying the contrast and noise reduction and its possible suppression of the background of the image. The techniques that were implemented are the modification of the contrast by lineal and non-lineal transformations, the histogram equalization technique, spatial filtering technique and a technique based on mathematical morphology operations. Finally, a contrast improvement index was applied in order to evaluate in a quantitative way each of the contrast enhancement technique implemented.

Image processing, Contrast enhancement, Mammographic images

Resumen

En este trabajo se presentan los resultados obtenidos de aplicar técnicas de mejora de contraste a regiones de interés extraídas de mamografías digitalizadas. El objetivo es mejorar la detección de lesiones mamarias, como por ejemplo las microcalcificaciones, y con esto contribuir a un diagnóstico temprano del cáncer de mama. Normalmente las imágenes de las regiones de interés adquiridas no presentan la más alta calidad, y tienen algunas deficiencias, que dificultan la detección de de las microcalcificaciones que se encuentran dentro de ellas. Debido a esto el enfoque en este trabajo es mejorar la calidad de la región de interés, realizando un realce de bordes y contornos, modificando el contraste, así como la reducción de ruido y eliminación del fondo de la imagen. Las técnicas que se implementaron fueron, la modificación de contraste basada en una transformación del tipo lineal y no lineal, una técnica conocida como ecualización del histograma, filtrado espacial y finalmente una mediante una técnica basada en operaciones de morfología matemática. Finalmente, un índice de mejora de imagen fue aplicado para evaluar de forma cuantitativa cada una de las técnicas de mejora de contraste implementadas.

Procesamiento de imagen, Mejora de contraste, Mamografías

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Introduction

Digital image processing is composed of a set of techniques that work on the digital representation of an image with the aim of highlighting objects that make it up to facilitate its analysis or subsequent manipulation by a user or through an artificial vision system.

In general, the image processing techniques are applied when it is necessary to make some modification, improve its appearance, enhance some characteristic of an object or when it is desired to detect, contrast or classify any object contained within it. Image enhancement techniques vary depending on the application.

Generally, they are based on the manipulation of gray levels, contrast enhancement, noise reduction, enhancement or reduction of edges and contour of objects, as well as the removal of the background of the image (Gonzalez & Woods, 2002).

In recent years, the development of medical images has evolved significantly and has revolutionized the diagnosis of many diseases. Medical images are considered as one of the most important and widely used tools in clinical medicine, because they have greatly facilitated the detection, diagnosis and study of affectations of the human body. In the case of mammography, it has undergone considerable improvements in recent years due to advances in technology associated with this type of image.

Due to this, mammography is currently considered as the most effective method to detect breast lesions that are not palpable, contributing to the early diagnosis of breast cancer and resulting in a decrease in the mortality rate between 25% and 30 % (Marrocco, et al., 2010).

Mammography presents a difficulty in interpretation because the microcalcifications present in it generally have a low contrast to the surrounding tissue (Cheng, et al., 2003). A solution to this problem is the application of one of the most commonly used imaging techniques in mammography known as enhancement or contrast enhancement.

Some of these improvements include some image processing techniques that contribute to specific tasks such as: enhancement of features such as borders or contours (Fu, et al., 2005) (Quintanilla-Domínguez, et al., 2009), contrast modification (Wirth, et al., 2004) in order to make analysis, noise reduction and background removal. The adaptive transformation function for the histogram is a technique that has been used in different applications such as, for example, the improvement of mammography images (Laine, et al., 1994), and the improvement of natural images (Jevtic, et al., 2009). In the work of (Vega-Corona, 2003), they use this technique in mammography ROI images, with the aim of attenuating the gray levels of the pixels with a small amplitude value, because the microcalcifications are presented with levels of high gray and, accordingly, it is in their interest to highlight those pixels with a gray level value larger than a threshold for discrimination.

The improvement of the contrast in mammography images has been used in different works with the specific objective of enhancing the microcalcifications of the surrounding tissue, in order to improve or make its detection easier, either by means of a system of detection or through a specialist. If it is by means of a detection system, there are some works that in their stage or stages of preprocessing or processing use mathematical morphology operations, among them the transformed Top-hat. Among these works, the following can be highlighted (Papadopoulos, et al., 2002), (Wirth, et al., 2004), (Ozgur, 2004), (Fu, et al., 2005), (Stojic, et al., 2005), (Halkiotis, et al., 2007), (Stojic & Reljin, 2010), which have obtained satisfactory results in terms of microcalcification detection.

In the present work, some image processing techniques are implemented in which an improvement of the contrast applied to digitalized mammography images is involved, with the aim of highlighting microcalcifications and improving their detection.

Image enhancement techniques

Image enhancement techniques are generally used to highlight some or some features that are of interest, in order to make it more likely to detect whether it is an automatic image analysis system and additionally simpler for visual recognition by human beings.

For the specific case of mammography images, these techniques are generally used to increase the contrast between regions containing pixels corresponding to microcalcifications and healthy tissue, that is, to highlight the edges of microcalcifications. Although microcalcifications are generally brighter than the surrounding tissue, in some cases where the breast is very dense, the contrast of some microcalcifications is so low that the human eye can barely distinguish them. The process of improving the contrast of microcalcifications is a very delicate process since a small improvement of the contrast can prevent a detection of the microcalcifications. On the other hand, a very high increase in contrast can significantly increase the amplitude of the background noise, which would lead to false detections (Wirth, et al., 2004).

Image enhancement techniques that are based on contrast modification can be classified into two types: indirect and direct. Those of indirect form are those techniques that modify the histogram of the image. Those of direct form are those techniques that are in charge of modifying directly the contrast of the image based on definite transformations. Another way to classify these techniques is to take into account global information, local information or both (Cheng, et al., 2003).

1. Contrast expansión

Contrast expansion is a technique that is based on point transformation operations or simply point operations. This technique works in the spatial domain and allows us to modify the contrast of the intensity levels in the image individually and conveniently. This technique takes an input image and generates an output image so that the intensity level of each output pixel depends on the intensity level of each input pixel. An important feature in a dot operation is that the coordinates of each output pixel correspond to the coordinates of the input pixel, which means that the dot operation does not modify the spatial position of the pixels. In a digital image, the pixel value represents the magnitude of an observed characteristic, such as the intensity level (brightness). The graphical representation of the intensity values that make up an image is known as the "histogram of the image".

The histogram of the image is a distribution function that shows the number of pixels for each intensity level where the abscissa corresponds to the intensity level and the ordinate is the frequency of occurrence in the image, that is, the number of pixels with that intensity level. The histogram of any image contains information that may be important so, in many cases, certain types of images are completely specified by their histogram.

The expansion of the contrast is sometimes called transformation of the intensity level, which in this case would be transformation of gray level since the images used for this work are in gray scale. By modifying the values of the intensity levels or gray levels of the image pixels, the image histogram is also modified. Usually, this technique is used when the histogram of the image is narrow, so it allows us to adjust the histogram to achieve a greater separation in the distribution of gray levels in the image. The histogram setting can be conditioned by a known transformation function T , which can be of linear or non-linear type. When the transformation function T is of the linear type, it can be defined as:

$$I_T(x, y) = T(I(x, y)) = I(x, y) * k + m \quad (1)$$

Where $I(x, y)$ is the gray level of a pixel of the input image I , I_T is the image resulting from the transformation, T represents the transformation function at the point (x, y) , k , m are constant values. When the transformation function is of the non-linear type, they are generally considered a type of non-decreasing (monotonous) functions. A characteristic of this type of functions is that they work in the mid-range of intensity levels, that is, they reinforce the intensity levels of the pixels in the mid-range, leaving dark pixels and bright pixels almost unchanged, such so that the histogram has a desired shape. An example of a non-linear type transformation function is defined as:

$$I_T(x, y) = T(I(x, y)) = I(x, y) + K * I(x, y)(L_{max} - I(x, y)) \quad (2)$$

Where L_{max} corresponds to the maximum intensity level of the original image and K determines the amount of increase ($K > 0$), or decrease ($K < 0$), in the mid-range of intensity levels.

a)

b)

c)

d)

Figure 1 Improved contrast of an ROI image by applying a non-linear type transforming. (a) Original image. (b) Image with enhanced contrast. (c) Histogram of gray levels of the original image. (d) Histogram of gray levels of the image with enhanced contrast

Figure 1 shows an image enhancement by contrast expansion by a non-linear type transformation function on an image of a region of interest (ROI) extracted from a mammogram. In the same figure it can be seen its original gray level histogram, as well as the new distribution of the histogram.

2. Adaptive transformation function for the histogram

The adaptive transformation function for the histogram is an image enhancement technique that, through a non-linear transformation function, allows us to modify the gray levels of an image. The non-linear transformation function is defined in Eq. (3) and was proposed in (Laine, et al., 1994). This technique allows us to control the contrast and threshold adaptively.

$$I_T = \alpha [\text{sigm}(k(I(x,y) - \beta)) - \text{sigm}(-k(I(x,y) - \beta))] \quad (3)$$

Where, $I(x, y)$ is the input image, I_T is the image resulting from the transformation, α is defined as:

$$\alpha = \frac{1}{\text{sigm}(k(1-\beta)) - \text{sigm}(-k(1+\beta))} \quad 0 < \beta < 1 \quad (4)$$

and $\text{sigm}(x)$ is defined as:

$$\text{sigm}(x) = \frac{1}{1+e^x} \quad (5)$$

Where β and k are the parameters that represent the threshold control and the contrast control in the image respectively. For an input image I , with a maximum gray level L_{max} , it is necessary to map the image in the range of $[-L_{max}, L_{max}]$ to an image in the range of $[-1, 1]$, according to this, the value of L_{max} can be used as a normalization factor in Eq. (3), as a consequence of this, values of β and k can be used independently of the dynamic range of the image. In addition, the following restriction must be met: $\beta k > 2$. Figure \ref{effect-func-imaROI} shows the improvement of the contrast of a ROI image by the non-linear transformation function defined in Eq. (3) using values of $\beta=0.2$ and $k=20$, which are obtained experimentally, in addition to generating good results in improving the contrast in ROI images.

a)

b)

c)

d)

Figure 2 Contrast enhancement of an ROI image by applying Eq. (3) with values of $k=20$ and $\beta=0.2$. (a) Original ROI image. (b) Image with enhanced contrast. (c) Histogram of gray levels of the original ROI. (d) Histogram of gray levels of the ROI with enhanced contrast.

3. Spatial Filtering

Spatial filtering in images is done through the convolution operation between a region of the image and a filter known as kernel, window or convolution mask. Regardless of the type of filter, the convolution operation consists of a sum of products between the coefficients of the filter and the intensities of the pixels that are inside the convolution mask at a point of interest in the image (Gonzalez & Woods, 2002). Among the most used applications with spatial filtering in mammography images are: contrast enhancement (Tiu, Jong, & Hsieh, 2008), edge detection (Fu, et al., 2005), as well as the detection of mammographic characteristics such as microcalcifications (Cheng, et al., 2004). Local image enhancement has been used in segmentation and image contrast enhancement applications. But this section only focuses on contrast enhancement applications. This technique improves the contrast of the mammographic characteristics (microcalcifications) of ROI images with different size and shape according to the changing environment. The procedure is to define a rectangular or quadrangular environment (also known as a mask or window) of a certain size (which can be fixed or variable) and move its center pixel to pixel, which can be adapted to local variations in the levels of grays. Generally for simplicity, the environment used is square and odd in size. An important feature of this technique is that it can improve the more anatomical details without the significant introduction of artifacts and has shown that it can identify microcalcifications in a ROI image with dense tissue, where the contrast between microcalcifications and tissue is quite low (Cheng, et al., 2003). This technique has been used in mammography images in works such as (Morrow, et al., 1992), (Vega-Corona, et al., 2003), (Vega-Corona, et al., 2006). According to (Veldkamp & Karssemeijer, 2000), a way to define the local contrast of a pixel in an image can be by using the following expression:

$$C_l(x, y) = I(x, y) - M_l(x, y) \quad (6)$$

Where $I(x, y)$, is the gray level of a pixel of the input image I , at the point (x, y) , $M_l(x, y)$ represents the average of the gray levels of a region of determined size with its center in the position (x, y) . For a region of size $m \times n$ centered on (x, y) , M_l is defined as:

$$M_I = \frac{1}{m \times n} \sum_{x=1}^m \sum_{y=1}^n I(x, y) \quad (7)$$

In Figure 3, an example of the local improvement of a ROI image is shown by means of the local contrast defined in Eq (6), using square windows of different sizes, 3×3 , 5×5 and 7×7 .

a)

b)

c)

d)

Figure 3 Local enhancement of a ROI image using the local contrast defined in Eq. (6). (a) Original image. (b) Improving the contrast of the ROI image using a 3×3 size window. (c) Improving the contrast of the ROI image using a 5×5 size window. (d) Improved contrast of the ROI image using a 7×7 size window.

4. Improvement by mathematical morphology

Mathematical Morphology (MM) is a very powerful tool in the analysis and digital processing of images. The MM is responsible for extracting, modifying and combining the components of an image that are useful in the representation and description of a region (Gonzalez & Woods, 2002). The identification of objects and their characteristics through their shape make the MM an appropriate approach for vision processes, image processing and pattern recognition. At present, there is a great diversity of applications related to image processing, in which the use of MM techniques has proved successful. Among the most important, segmentation can be mentioned (Sulehria, et al., 2007), (Fu, et al., 2005), contrast enhancement (Halkiotis, et al., 2007), (Mendiola-Santibañez, et al., 2007) and edge detection (Jiang, et al., 2007), (Cheng & Xu, 2002).

Originally, MM-based operations were developed for binary images and subsequently extended to gray-level images, such as the ROI images analyzed in this work. According to the above, the use of morphological operations will focus only on images in gray levels. Morphological operations allow extracting geometric structures from an image I to transform or improve them according to some predefined objective. Generally, a processing operator known as a structuring or structuring element (SE) is used for this. The SE is a completely defined set that is characterized by its shape and size and that has a reference point known as origin. Generally, the SE is much smaller than the image with which it will interact. In addition, the shape and size of the SE are defined according to the purpose of the application.

The best known basic morphological operations are erosion and dilation. The combination of these operations is the basis for creating other operations, which are also used in image processing applications such as segmentation, edge detection, smoothing, etc. But the application that will be very useful for this work is the improvement of contrast. In order to perform this task, the use of a technique known as Top-hat transform is proposed.

According to (Wirth, et al., 2004), the principle of contrast enhancement through the use of morphological operations was introduced by (Soille, 1997) as an extension to modify the contrast of an image. The improvement of the contrast of an image by applying mathematical morphology can be done through the Top-hat transform proposed by (Meyer, 1979). The Top-hat transform is a type of residual filter since it is made up of a difference between two basic transformations. In general, the Top-hat transform consists of highlighting those regions of the image that have been eliminated by the opening operation.

One of the main features of the Top-hat transform is that it is used to highlight locally bright objects within an image. This is because, first, the opening operation is responsible for reducing the bright details within the image.

Then, by means of the difference between the original image and the image modified by the opening, a new image is obtained with the objects or regions highlighted. That is, in the transformed image the contrast improvement of the objects or regions that were eliminated by the opening operation is obtained. In accordance with the above, it makes specifically the Top-hat transform by opening an excellent option to modify the contrast of the ROI images and, consequently, enhance the microcalcifications with respect to the surrounding tissue. The Top-hat transform is defined as the difference between the original image I and the opening of the original image using a SE :

$$I_{TH} = I - (I \circ SE) \quad (8)$$

where $(I \circ SE)$, represents an operation that opens, defined as the erosion of I by SE followed by a dilation using the same SE , the opening can be expressed as:

$$(I \circ SE) = (I \ominus SE) \oplus SE \quad (9)$$

Where $\ominus$ represents an erosion operation and $\oplus$ represents an expansion operation.

Different examples of ROI images processed by the Top-hat transform using different sizes of SE are shown in Figure 4.

In Figure 4 it can be seen that the contrast of the images has been modified, allowing a better visualization of the microcalcifications present in the images, fulfilling the objective of improving the image.

Figure 4 Images processed using the Top-hat transform. (a) - (d) Original ROI images. (e) - (h) ROIs processed with a $SE 7 \times 7$

Evaluation of image enhancement techniques

One of the problems of image enhancement techniques is the quantification of the performance of the technique used, that is, to have an evaluation criterion that proves that there really was an improvement, compared to some other technique used with the same objective (Cheng, et al., 2003). In the literature corresponding to image enhancement using contrast enhancement or enhancement techniques, most authors agree that the performance of the techniques is characterized by a direct visual inspection process. On the other hand, in order to make another type of comparison of image improvement techniques, in different works some methods have been proposed to evaluate the improvement in a quantitative way. In this work, a method called contrast improvement index (CII) will be used, which was proposed by (Laine, et al., 1994) and has been used in different works such as (Kang & Zhang, 2009), (Yoon & Ro, 2002), as a measure of the performance of contrast enhancement in mammography images. The CII is defined as:

$$CII = \frac{C_{IP}}{C_{IO}} \tag{10}$$

Where, C_{IP} and C_{IO} correspond to the contrasts of the enhanced ROI image and the original ROI image, respectively. The C contrast of a region with microcalcifications is defined as:

$$C = \frac{f-b}{f+b} \tag{11}$$

Where, f and b represent the average of the gray values of the region with microcalcification and the average of the gray values of the tissue region, respectively. The larger the value of the CII, the greater the performance of the technique. To perform the quantitative comparison of the contrast improvement of the ROI images of Figure 4, the CII defined in Eq. (10) is obtained, for the following contrast enhancement techniques presented in this work.

Image	Contrast Enhancement Technique			
	EC	FTANL	CL	Top-hat
Fig. 4(a)	0.5467	0.6158	0.5794	0.9531
Fig. 4(b)	0.5597	0.2382	0.7508	1.2906
Fig. 4(c)	1.0350	0.7735	0.9932	1.0368
Fig. 4(d)	0.8747	0.9795	0.9072	1.0033

Table 1 CII values obtained with contrast enhancement techniques for ROI images in Figure 4

Conclusions

According to the results obtained from the CII for the image enhancement techniques analyzed, it can be seen that the contrast enhancement applying the Top-hat transform for the ROI images was the best. Taking into account one of the main characteristics of the Top-hat transform, the improvement of the contrast of locally bright objects or regions within an image by means of an appropriate choice of SE in addition to the performance obtained through the CII, converts the Top-hat transform in a very good option to modify the contrast of ROI images in accordance with the objective set for this stage of the proposed system, which consists in enhancing microcalcifications with respect to the surrounding tissue.

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