Computers in Biology and Medicine 80 (2017) 14–23

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/cbm

A contrast enhancement method for improving the segmentation of breast lesions on ultrasonography

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A R T I C L E I N F O

Keywords:
Breast ultrasound
Contrast enhancement
Sigmoidal mapping function
Adaptive enhancement
Segmentation

A B S T R A C T

Purpose: This paper presents an adaptive contrast enhancement method based on sigmoidal mapping function (SACE) used for improving the computerized segmentation of breast lesions on ultrasound.

Methods: First, from the original ultrasound image an intensity variation map is obtained, which is used to generate local sigmoidal mapping functions related to distinct contextual regions. Then, a bilinear interpolation scheme is used to transform every original pixel to a new gray level value. Also, four contrast enhancement techniques widely used in breast ultrasound enhancement are implemented: histogram equalization (HEQ), contrast limited adaptive histogram equalization (CLAHE), fuzzy enhancement (FEN), and sigmoid based enhancement (SEN). In addition, these contrast enhancement techniques are considered in a computerized lesion segmentation scheme based on watershed transformation. The performance comparison among techniques is assessed in terms of both the quality of contrast enhancement and the segmentation accuracy. The former is quantified by the measure, where the greater the value, the better the contrast enhancement, whereas the latter is calculated by the Jaccard index, which should tend towards unity to indicate adequate segmentation.

Results: The experiments consider a data set with 500 breast ultrasound images. The results show that SACE outperforms its counterparts, where the median values for the measure are: SACE: 139.4, SEN: 68.2, HEQ: 64.1, CLAHE: 62.8, and FEN: 7.9. Considering the segmentation performance results, the SACE method presents the largest accuracy, where the median values for the Jaccard index are: SACE: 0.81, FEN: 0.80, CLAHE: 0.79, HEQ: 77, and SEN: 0.63.

Conclusion: The SACE method performs well due to the combination of three elements: (1) the intensity variation map reduces intensity variations that could distort the real response of the mapping function, (2) the sigmoidal mapping function enhances the gray level range where the transition between lesion and background is found, and (3) the adaptive enhancing scheme for coping with local contrasts. Hence, the SACE approach is appropriate for enhancing contrast before computerized lesion segmentation.

1. Introduction

Although several definitions about contrast can be found, for the purpose of this study, contrast is defined as the difference in intensity of adjacent regions of the image [1]. In breast ultrasound, the contrast between a potential lesion and its adjacent tissue should be easily perceived for image analysis purpose [2]. Nevertheless, the ultrasound image quality (e.g., resolution and contrast) is generally limited due to different factors such as shadowing, reverberation, speckle, noise, etc., which are originated from the physical phenomena of image acquisition and imperfections of the imaging system [3]. In addition, the success of the imaging procedure is highly operator dependent [4]. Thus, image enhancement techniques are used to increase the observability of subtle features in the image [2]. In this sense, a contrast enhancement stage is recommended to improve computer-aided processes like lesion segmentation [5], mainly, in gradient-based segmentation methods that attempt to find the largest intensity change between the lesion's margin and its surrounding tissue. Some approaches of these kind of methods for breast ultrasound are based on active contour models [6–8], radial gradient measurements [9,10], and morphological operators [11,12]. Also, segmentation methods for three-dimensional breast ultrasound usually apply a contrast enhance-

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http://dx.doi.org/10.1016/j.compbiomed.2016.11.005
Received 21 May 2016; Received in revised form 10 November 2016; Accepted 12 November 2016

ment stage before lesion segmentation [13,14].

Generally, contrast enhancement is performed by an intensity transformation, where an input pixel value is mapped into a new one by means of a mapping function [15]. In this context, histogram equalization [16,17] is often applied on breast ultrasound images [18–24]. This method is suitable for overall enhancement because it creates an intensity mapping function by considering all pixel data in the image. However, local brightness features in the input image could be unpreserved, that is, intensity levels with very high occurrence usually dominate over the lower ones. Additionally, when the contrast of homogeneous regions increases, the background noise could also increase noticeably [15]. To overcome this limitation, contrast limited adaptive histogram equalization (CLAHE) [25] has been used in breast ultrasound images [10,26]. In CLAHE, contextual regions are enhanced from local transformation functions, where a clip level imposes a maximum number of pixels for every gray level in the image. Hence, the enhancement is reduced in uniform regions of the image, which prevents over enhancement of noise.

Because breast ultrasound images present some degree of fuzziness, such as indistinct borders, ill-defined mass shapes and different tumor densities, fuzzy enhancement has been applied [5]. Commonly, fuzzy enhancement techniques transform the image histogram to the fuzzy domain using a fuzzy membership function such as the S-shaped function [27]. In general, fuzzy enhancement is based on four steps: gray-level normalization, image fuzzification, contrast enhancement, and image defuzzification [5,28]. The basic difference among fuzzy enhancement methods is found in the third step. For instance, Guo et al. [5] performed contrast enhancement by incorporating edge and texture information, whereas Taghvatalab and Faez [28] divided the fuzzy histogram into multiple sub histograms aiming to preserve image brightness.

Similarly to the S-shaped function, the sigmoid function has been used to enhance the tumor contrast in breast ultrasound images [29–31]. This non-linear mapping enhances a specific set of intensity values related to the tumor region and progressively decreases the values outside the region.

Since ultrasound images are inherently corrupted by speckle artifact and shadows, a contrast enhancement technique should be capable of enhancing the tumor region considering the local contrast, independently of the strength of the local noise. However, excepting CLAHE, the above mentioned methods process the image globally, that is, the local contrast is neglected. Also, they compute the mapping function directly from the speckled image, where spurious peaks in the gray level histogram could distort the mapping function. In addition, some techniques require parameter adjusting (e.g., level clip or distortion factors), which are defined heuristically.

In this paper, an adaptive contrast enhancement technique for improving the computerized segmentation of breast lesions on ultrasound is presented. The performance of the proposed technique is compared with four published contrast enhancement techniques often used for enhancing breast ultrasound images. Such comparison is performed in terms of both the quality of contrast enhancement and the computerized segmentation accuracy.

2. Basic concepts

2.1. Intensity transformation

Generally, given an input image with L gray-level values, contrast enhancement is performed by an intensity transformation that maps an input pixel value, g, into a new one, g'. Both pixel values are related by the expression $g' = T(g)$, where $T(g)$ is a transformation (or mapping) function applied to the original gray level g [15].

For creating the transformation function, the gray level probability density function (PDF) in the range $[0, L-1]$ is analyzed, where g=0 represents black and $g = L-1$ represents white. The PDF is given by $p(g) = n_g/N$, where n_g is the number of pixels in the image with intensity g and N is the total number of pixels in the image. Note that the discrete function $h(g) = n_g$ represents the image histogram; therefore, $p(g) = h(g)/N$ and $\sum_{g=0}^{g=L-1} p(g) = 1$.

A transformation function should satisfy the following two conditions [15]:

(a) $T(g)$ is a monotonically increasing function in the interval $0 \le g \le L-1$, and
(b) $0 \le T(g) \le L-1$ for $0 \le g \le L-1$,

where condition (a) preserves the order of intensity levels to prevent artifacts created by reversals of intensity, whereas condition (b) guarantees the same range of input and output intensities.

2.2. Bilinear interpolation

In adaptive contrast enhancement techniques, such as CLAHE, a transformation function is applied on a suitable number of blocks or tiles to avoid noise amplification in homogeneous areas [25]. To speed up the contrast enhancement procedure, non overlapped contextual regions are processed. However, if each region is mapped only by its own transformation function, an undesirable 'blocky' effect could appear. To overcome this effect, a sampling and interpolation scheme is proposed by Pizer et al [32].

First, sampling points are defined over the entire image, whose locations are usually at the center of contextual regions. Then, every original pixel in the image, g, is transformed by the gray level distributions of the neighboring contextual regions as illustrated in Fig. 1. Let A, B, C, and D be the center points of the surrounding contextual regions, whose corresponding transformation functions are denoted as $T_A(g)$, $T_B(g)$, $T_C(g)$, and $T_D(g)$, respectively. The new pixel gray level, g', is calculated by bilinear interpolation of its neighboring transformation functions as [25]:

$$g' = (1-y)[(1-x)T_A(g) + xT_B(g)] + y[(1-x)T_C(g) + xT_D(g)], \quad (1)$$

where x and y are normalized distances with respect to point A.

3. Proposed approach

The proposed adaptive contrast enhancement method involves: computing an intensity variation map, calculating a sigmoidal mapping function for each contextual region in the intensity variation map, and

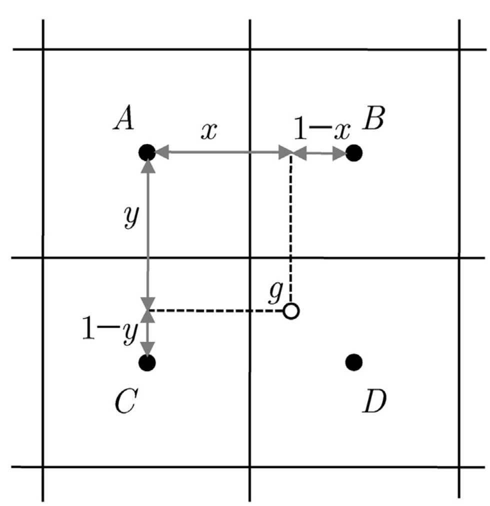

Fig. 1. Sampling and interpolation scheme used for adaptive contrast enhancement. Points A, B, C, and D represent the centers of contextual regions and g is the point to be interpolated by the linear combination of the transformation functions $T_A(g)$, $T_B(g)$, $T_C(g)$, and $T_D(g)$.