

# MULTISCALE CONTRAST ENHANCEMENT OF MEDICAL IMAGES

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## ABSTRACT

We presents results obtained by different contrast enhancement methods applied to medical images. We take into account classical histogram specification, local and wavelet-based techniques and a novel approach for multiscale contrast enhancement. The latter, whose rationale grounds in theories of visual perception, exploits a local definition of the Fechner-Weber's contrast within the context of a non-linear scale-space representation generated by anisotropic diffusion. Our experimental fields concerns a difficult kind of medical images, namely digital mammographic images.

## 1. INTRODUCTION

Our work focuses on contrast enhancement methods that address the issue of using a multiscale representation.

One such method was proposed in [1], with the aim of overcoming the limits of classical techniques and of encompassing advantages of multiresolution approaches.

Actually, classical methods try to enhance the contrast of the input image without measuring the contrast itself. A well known case is histogram specification [2].

Adaptive methods, on the contrary, take into account a contrast  $C(x,y)$  locally defined. Beghdadi and Le Negrate [3] have refined such approach so as to embed the estimate of object edges while computing  $C(x,y)$ . For a given pixel  $(x,y)$ , they calculate

$$\bar{E}(x,y) = \frac{\sum_{(i,j) \in R_B} \Delta(i,j) I(i,j)}{\sum_{(i,j) \in R_B} \Delta(i,j)} \quad (1),$$

This work is partially supported by Inforsud-Bull HN Contract.

where  $\Delta(i,j) = |I(i,j) - \bar{I}_B|$ ,  $I(x,y)$  being the luminance of pixel  $(x,y)$  and  $\bar{I}_B(x,y) = \frac{\sum_{i,j \in R_B} I(i,j)}{n}$  the average luminance of the local background  $R_B$  surrounding  $(x,y)$ ;  $n$  gives the dimension of  $R_B$ . The local contrast becomes

$$C(x,y) = \frac{|I(x,y) - \bar{E}(x,y)|}{|I(x,y) + \bar{E}(x,y)|} \quad (2).$$

Enhancement is obtained as  $C'(x,y) = f_{enh}(C(x,y))$  where  $f_{enh}$  is chosen so that  $C(x,y) \in [0,1]$ ,  $f_{enh}(C(x,y)) > C(x,y)$  and  $f_{enh}(C(x,y)) \in [0,1]$ . The enhanced values  $I_{enh}(x,y)$  come from inversion of Eqn. 2. One critical aspect of the method is the choice of the  $R_B$  dimension, i.e. the size of the window in which  $C(x,y)$  is estimated. Indeed it would be appealing to average such estimate over a range of windows of different size, thus achieving a sort of multiple scale estimate.

Recently, such kind of issue has been stressed by wavelet based methods [4,5]. Special attention has been devoted to schemes relying upon the multiscale edge representation originally developed by Mallat and Zhong [6]. Namely, they define two oriented wavelets

$$\psi^1(x,y) = \frac{\partial}{\partial x} \phi(x,y) \quad \psi^2(x,y) = \frac{\partial}{\partial y} \phi(x,y) \quad (3),$$

where  $\phi(x,y)$  is a smoothing function. Under the assumption that the image is a differentiable 2-D function

$I(x,y) \in L^2(\mathbb{R}^2)$ , the associated dyadic wavelet transform (WT) of  $I$  at scale  $2^j$ , at position  $(x,y)$  and in orientation  $k$  is:

$$W_{2^j}^k[I(x,y)] = I(x,y) * \psi_{2^j}^k(x,y), \quad k=1,2 \quad (4),$$

with  $\psi_{2^j}^k(x,y) = 2^{-2j} \psi^k(2^{-j}x, 2^{-j}y)$ . Eqn. 4 produces a sequence of gradients of  $I(x,y)$  smoothed by  $\phi(x,y)$  at dyadic scales. These are named the multiscale gradients  $\nabla_{2^j} I(x,y)$ . In such framework, contrast between objects and regions can be enhanced through transformation of edge gradients followed by reconstruction. It has been shown (Lu and Healy, [4]) that is possible to enhance contrast in the form

$$v_j(x,y) = k_j \cdot g_j(u_j) \quad (5).$$

Namely,  $k_j$ ,  $g_j(\cdot)$ , and  $u_j$  represent a parameter, a transformation function and the normalized gradient magnitude respectively, all depending on scale  $2^j$ . Taking  $g_j(x)=x$ , a linear “stretching” transformation results. In general, different transformations at different scales can be designed by Eqn. 5.

## 2. MULTISCALE ENHANCEMENT

In this Section, we give a review of the method presented in [1]. The Fechner-Weber’s law defines the image contrast as  $C = \ln(L_T/L_B)$ , where  $L_T$  and  $L_B$  are the luminances of a plain target and a plain background, respectively. Such ideal relationship no longer holds when either target or background is structured (e.g. Figure 1(a)). In complex images it is necessary to take into account two properties concerning perceived contrast: it varies locally across the image; it is very sensitive to edges. In order to deal with first property, we exploit the concept of scale. The F-W law is modified so that  $L_T$  becomes the luminance  $I(x,y,t)$  of point  $(x,y)$  at scale  $t$  (the local target);  $L_B$  is the average luminance  $\bar{I}_B(x,y,t) = \sum_{i,j \in R_B} I(i,j,t)/n$  of the local background  $R_B$  at scale  $t$ . This yields to the local contrast at scale  $t$

$$C(x,y,t) = \ln(I(x,y,t) / \bar{I}_B(x,y,t)) \quad (6).$$

We assume the optimal local contrast  $C_{opt}(x,y)$  is the contrast  $C(x,y,t_{opt})$ , computed at the optimal scale  $t_{opt}$  selected among multiple scales. The multiscale representation is built up by evolving a diffusion equation over the original image. To design an edge sensitive contrast enhancement (the second property), a non-linear scale-space is generated by the anisotropic diffusion equation [7]

$$\frac{\partial I(x,y,t)}{\partial t} = \text{div}(D(x,y,t) \cdot \nabla I(x,y,t)) \quad (7),$$

where  $\nabla$  indicate the gradient operator. In this case, the diffusion coefficient  $D(x,y,t) = g(\|\nabla I\|)$  inhibits diffusion when local brightness transition is significant.

Scale  $t_{opt}$  is selected as follows. Consider an image containing targets of different brightness on a dark background. Each target will exhibit an optimum contrast response at a certain scale between the initial scale and a late evolution. The optimal scale will correspond to the scale where noisy background has been smoothed, but yet diffusion has not blurred the target itself. Notice that for each point  $(x,y)$  of the image, Eqn. 6 describes a contrast  $C(x,y,t) = C_{x,y}(t)$  evolving as a function of scale  $t$ . We can assume the range of scales of interest is an interval, say,  $0 \leq t_{inf} \leq t < t_{sup} < \infty$ , since in principle scale  $t$  spans the whole real line but in practice this is never the case. Thus  $C_{x,y}$  has a finite norm and, owing to scale-space causality property, it is continuous and concave. The optimal contrast can be chosen as

$$C_{opt}(x,y) = \max_{t \in [t_{inf}, t_{sup}]} |C_{x,y}(t)| \quad (8).$$

$C_{opt}(x,y)$  is then enhanced by a function  $f_{enh}$ :

$$C_{enh}(x,y) = f_{enh}(C_{opt}(x,y)) \quad (9).$$

Eqn. 6 can be inverted as a function of  $C$ ; at each point  $(x,y)$  the enhanced output grey value  $I_{enh}(x,y)$  is eventually calculated by substituting  $C$  with  $C_{enh}$  according to Eqn. 9, hence:

$$I_{enh}(x,y) = \bar{I}_B(x,y) \exp(C_{enh}(x,y)) \quad (10)$$

where  $\bar{I}_B(x,y) = \bar{I}_B(x,y,t_{opt})$ . The proposed method has a straightforward implementation by discretizing Eqn. 7 on a square lattice and choosing  $n = \text{dim}(R_B) = 4$ .

## 3. EXPERIMENTAL WORK AND DISCUSSION

In this Section we provide an example of experimental results obtained applying above discussed methods to mammograms provided by courtesy of Istituto di Fisica Sanitaria of Sant’Orsola Malpighi Hospital (Bologna, Italy). All images are digitized at 300 dpi, at a resolution of 12 bit/pxl, successively windowed to 8 bit/pixel, using a VIDAR VXR-12 scanner.

The experiments that have been performed can be summarized as follows.

- Method 1: Histogram specification. Rayleigh distribution

- Method 2: Locally adaptive contrast enhancement (Beghdadi - Le Negrate)  
Enhancement function  $f_{enh} = \ln(1+k \cdot C_{opt})$ ,  $k=2$ .
- Method 3: Wavelet based multiscale edge representation (Lu and Healy).  
4 decomposition scales; scale adaptive stretching function ( $k_j = 1/j$ , to enhance details)
- Method 4: Scale space contrast enhancement  
 $g = \frac{1}{5} \|\nabla I\|^{-\frac{3}{5}}$ , favoring diffusion with backward sharpening across edges,  $f_{enh} = \ln(1+k \cdot C_{opt})$ ,  $k=2$ .

The performance of each method has been globally characterized by measuring the Shannon's entropy and locally evaluated by assessing the behavior of a scan line profile. Actually, enhancement techniques that lead to higher entropy are likely to extract the more relevant information. It has to be noticed however that statistical measures like entropy can characterize global enhancement, but they lack of accuracy in local contrast evaluation. To this end a complementary control can be performed on a sample scan line intensity profile taken from a cross-section of a local region of interest.

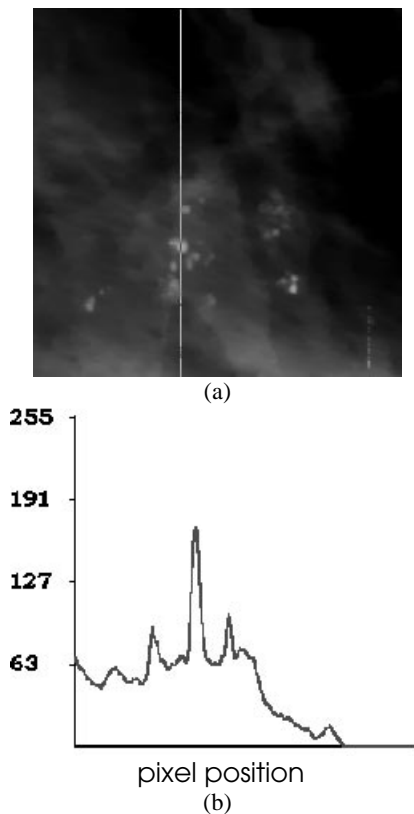


Figure 1: (a) original image (microcalcification cluster), with superimposed the selected scan line [(x1=102, y1=0), (x2=102, y2=255)]; (b) scan line profile

In the following we provide an example which is representative of average results. The example uses the image shown in Figure 1(a). The entropy of this image is 6,167741 bits. Figure 1(b) shows its scan line profile.

Entropies measured in contrast enhanced images are given in Table 1.

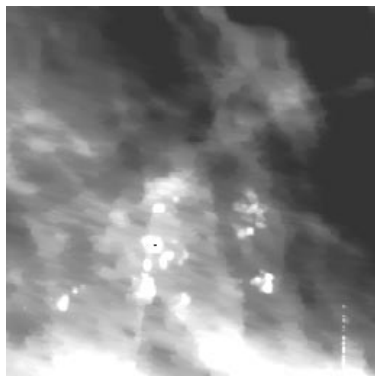
Table1: Entropy of enhanced images

Enhancement method	Enhanced Images	Entropy (bits)
1	2 (a)	5,970697
2	2 (b)	6,190469
3	2 (c)	6,107545
4	2 (d)	6,926772

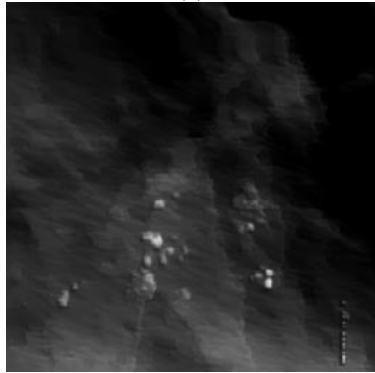
Figures 2 (e), (f), (g), (h) report typical results obtained by profile evaluation. It can be seen that the scale-space method improves contrast by local enhancement of edges while maintaining the overall shape of line profile; notice that background noise is not enhanced. In conclusion, the proposed approach encompasses advantages peculiar to locally adaptive techniques and techniques based on WT. Its performance is due to the following features: capability of estimating local contrast over a range of scales; exploitation of edge information; noise amplification control due to the anisotropy of the diffusion process.

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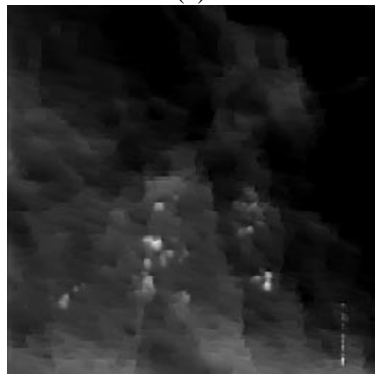
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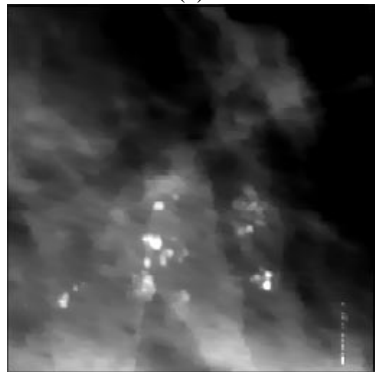
(a)



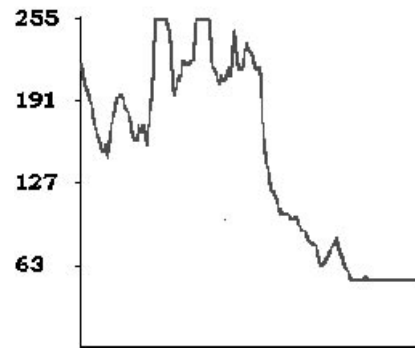
(b)



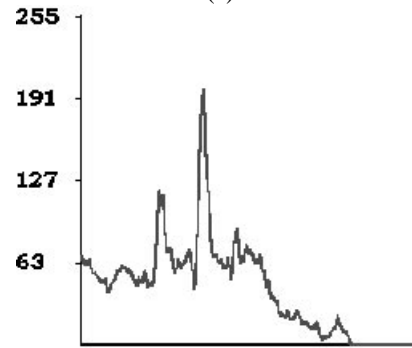
(c)



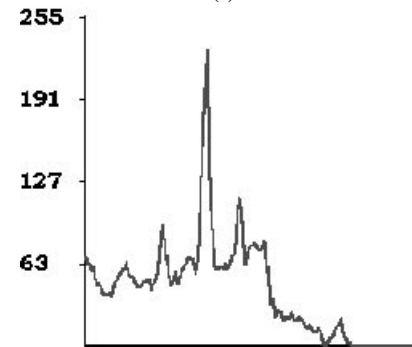
(d)



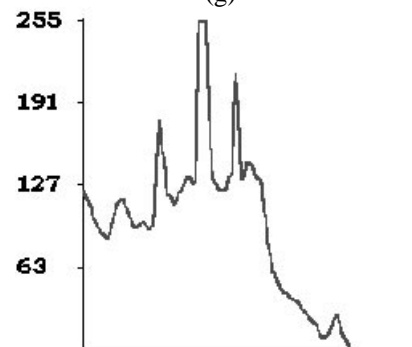
(e)



(f)



(g)



(h)

Figure 2: (a), (b), (c), (d) show images enhanced by the different methods 1, 2, 3, and 4. (e), (f), (g), (h). plot the profiles of the same selected scan line chosen in Figure 1(b) [ $x_1=102, y_1=0, x_2=102, y_2=255$ ], but measured on images (a), (b), (c), (d).