MEDICAL IMAGE ENHANCEMENT USING THRESHOLD DECOMPOSITION DRIVEN ADAPTIVE MORPHOLOGICAL FILTER

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ABSTRACT

One of the most common degradations in medical images is their poor contrast quality. This suggests the use of contrast enhancement methods as an attempt to modify the intensity distribution of the image. In this paper, a new edge detected morphological filter is proposed to sharpen digital medical images. This is done by detecting the positions of the edges and then applying a class of morphological filtering. Motivated by the success of threshold decomposition, gradient-based operators are used to detect the locations of the edges. A morphological filter is used to sharpen these detected edges. Experimental results demonstrate that the detected edge deblurring filter improved the visibility and perceptibility of various embedded structures in digital medical images. Moreover, the performance of the proposed filter is superior to that of other sharpener-type filters.

1. INTRODUCTION

Today, there is almost no area of technical endeavour that is not impacted in some way or another by digital image processing. The area of digital image processing is a dynamic field and new techniques and applications are reported routinely in professional literature and in new product announcements. Digital images are subject to a wide variety of distortions which may result in visual quality degradations. Image enhancement is crucial for many image processing applications. The ultimate goal of image enhancement techniques is to improve the visual information of a degraded image in a subjective process.

Image sharpening is a classic problem in the field of image enhancement. The principal objective of image sharpening is to highlight fine details in an image or to enhance details that have been blurred, either in error or as a natural effect of a particular method of image acquisition. Usages of image sharpening vary and include applications ranging from document and medical imaging to industrial inspection and autonomous guidance in military systems [1].

Linear operators have been the dominating filter class throughout the history of image processing. This is triggered by the computational efficiency of linear filtering algorithms. Despite the elegant linear system theory, not all image sharpening problems can be satisfactorily addressed through the use of linear filters. Many researchers now hold the view that it is not possible to obtain major breakthroughs in image sharpening without resorting to nonlinear methods [2].

Identifying the edges of low contrast structures is one of the most common tasks performed by those interpreting medical images. Low contrast structures need to be resolved in all kinds of digital medical images; e.g., X-ray imaging, computed tomography (CT), magnetic resonance (MR), digital mammography, ultrasound, angiography and nuclear medicine [3].

X-rays are the oldest and the most frequently used form of medical imaging. X-ray is a painless medical test, which helps physicians diagnose and treat medical conditions. This medical test involves exposing a part of the body to a small dose of ionizing radiation with the objective of producing pictures for the inside of the body. The bone X-ray makes images of any bone in the body, including the hand, wrist, arm, foot, ankle, knee, leg or spine. X-ray images are maintained as hard film copy or, more likely, as a digital image that is stored electronically. These stored images are easily accessible and are sometimes compared to current X-ray images for diagnosis and disease management [4].

Most medical images contain important structures, which are characterized with low natural contrast with the surrounding structures. To obtain high contrast in the raw image directly from the imaging device is almost always expensive in examination time or X-ray dose to the patient. Thus, the production of these images generally involves a compromise between the need for enhanced contrast and its related costs. In these situations, digital post-processing can play a very important role [3].

Mathematical morphology is the name given to a geometrical branch of nonlinear filters. It offers a unified and powerful approach to numerous image processing problems. One of the most appealing aspects of morphological image processing lies in addressing the image sharpening problem [5].

In this paper, a new method for sharpening low constrast X-ray imaging is proposed. This is utilised by sharpening medical images by extending the edge-detected morphological filter first introduced in [6] for image deblurring. This is done by detecting the positions of the edges and then applying a class of morphological filtering. Since the edge is a prominent feature of an image, it is a vital foundation for medical image sharpening.

Section 2 introduces the threshold decomposition and the method used for edge detection. Morphological filtering for medical image sharpening is explained in Section 3. Section 4 will present in detail the proposed sharpening filter. Then, this proposed filter is tested on several X-ray examples and its performance is compared with that of other sharpener-type filters. Finally, Section 5 contains some concluding remarks.

2. BACKGROUND

2.1 Threshold Decomposition

Threshold decomposition is a powerful theoretical tool, which is used in nonlinear image analysis. Many filter techniques have been shown to 'commute with thresholding'. This means that the image may be decomposed into a series of binary levels, each of which may be processed separately. These binary levels can then be recombined to produce the final greyscale image with identical pixel values to those produced by greyscale processing. Hence a greyscale operation may be replaced by a series of equivalent binary operations. The first threshold decomposition framework for image processing was introduced by Fitch et al. in [7]. This was capable of modelling a wide range of filters based on rank ordering such as the median and WOS operators. It was also capable of modelling linear FIR filters with positive weights. The framework was limited to modelling low pass filters or 'smoothers'.

More recently the framework was modified by Arce in [8]. This modification introduced the ability to model both linear and nonlinear filters with negative as well as positive filter weights. It in effect opened up the possibility to model high pass and band pass filters as well as low pass filters.

Motivated by this success an image sharpening technique is developed and implemented through a framework of threshold decomposition. Consider an integer-valued set of samples $x_1, x_2, \dots, x_n$ forming the signal $X = (x_1, x_2, \dots, x_n)$ where $x_i \in \{-m \dots, -1, 0, 1, \dots, m\}$. The threshold decomposition of X amounts to decomposing this signal into $2m$ binary signals $X^{-m+1}, \dots, X^0, \dots, X^m$, where the ith element of x^m is defined by Equation (1):

$$x_i^m = \begin{cases} 1 & if\ x_i \geq m \\ -1 & if\ x_i < m \end{cases} \tag{1}$$

The above threshold decomposition is reversible, such that if a set of threshold signals is given, each of the samples in X can be exactly reconstructed as shown in Equation (2):

$$x_i = \frac{1}{2} \sum_{j=-m+1}^{m} x_i^j \tag{2}$$

Thus, an integer-valued discrete-time signal has a unique threshold signal representation, and vice versa.

2.2 Edge Detection

Edge detection is a fundamental tool, which is commonly used in many image processing applications. This process detects boundaries between objects and background in the image. An edge-detection filter can be used to improve the appearance of blurred or low-contrasted images.

Since edge detection has been an active area for more than 40 years, many effective methods have been proposed such as gradient edge detectors (1st derivative), zero crossing (2nd derivative), Laplacian of Gaussian (LOG) and Gaussian edge detectors [9].

In spite of all these efforts, none of the proposed operators are fully satisfactory in real world applications. They do not lead to satisfactory results when used as a means of identifying locations at which to apply image sharpening. In this paper, the enhancement is applied through a framework of threshold decomposition. This has two advantages: it reduces the edge detection to a simple binary process; and it makes the estimation of edge direction straightforward. Edge detection and direction estimation may be carried out by identifying simple patterns, which are closely related to the Prewitt operators [10]. The operators are sometimes called compass operators because of their ability to determine gradient direction. The gradient is estimated in 8 possible directions (for a 3×3 mask) with a difference of 45° between each direction. The first 4 operators are the four (3×3 mask) shown in Figure 1, the other four can be obtained by applying a 45° clockwise rotation. By using the 8 masks of the Prewitt operators, thick edges in the 8 directions can be detected.

$$h_1 = \begin{bmatrix} 1 & 1 & 1 \\ D_0 & D_1 & D_2 \\ -1 & -1 & -1 \end{bmatrix} \quad h_2 = \begin{bmatrix} D_0 & 1 & 1 \\ -1 & D_1 & 1 \\ -1 & -1 & D_2 \end{bmatrix}$$

$$h_3 = \begin{bmatrix} -1 & D_0 & 1 \\ -1 & D_1 & 1 \\ -1 & D_2 & 1 \end{bmatrix} \quad h_4 = \begin{bmatrix} -1 & -1 & D_0 \\ -1 & D_1 & 1 \\ D_2 & 1 & 1 \end{bmatrix}$$

Figure 1 - Four (3×3 mask) of Prewitt operators

where $g = \{D_0, D_1, D_2\}$ is the structuring element used in mathematical morphology and will be explained later.

On the other hand, the 8 masks mentioned in [11] can be used to detect thin edges in the 8 directions. The first 4 operators are represented by the four (3×3 mask) shown in Figure 2, the other four can be obtained by negating the elements of these matrices.

$$k_1 = \begin{bmatrix} -1 & -1 & -1 \\ 1 & 1 & 1 \\ -1 & -1 & -1 \end{bmatrix} \quad k_2 = \begin{bmatrix} 1 & -1 & -1 \\ -1 & 1 & -1 \\ -1 & -1 & 1 \end{bmatrix}$$

$$k_3 = \begin{bmatrix} -1 & 1 & -1 \\ -1 & 1 & -1 \\ -1 & 1 & -1 \end{bmatrix} \quad k_4 = \begin{bmatrix} -1 & -1 & 1 \\ -1 & 1 & -1 \\ 1 & -1 & -1 \end{bmatrix}$$

Figure 2 - Four (3×3 mask) for thin edge detection

With the aid of the threshold decomposition described above, and for each level, the edges are detected by searching for patterns of grey levels consistent with the 8 masks of the Prewitt operators for thick edges, and the 8 masks mentioned in [11] for thin edges. Thus the sharpening filter is applied only at these detected edges rather than all the pixels of the image.

3. IMAGE SHARPENING BY MORPHOLOGICAL FILTERING

Kramer and Bruckner in [12] define a nonlinear transformation for sharpening digitized greyscale images. The transformation replaces the grey level value at a pixel by either the minimum or the maximum of the grey level value in its neighbourhood. The choice is dependent on which one is closer in value to the original grey level intensity.

In mathematical morphology, the transformation which replaces the grey level value at a pixel by the maximum of the grey level value in its neighbourhood is the greyscale dilation operator as defined in Equation (3):

$$(f \oplus g)\ (z) = \max_{\mu \in R^2} \left[f(\mu) + g(z-\mu) \right] \tag{3}$$

in which function $f\,(x), f : x \in R^2 \rightarrow f\,(x) \in R$ is the original image, and $g\,(x), g : x \in R^2 \rightarrow g\,(x) \in R$ is the structuring element implicitly defining the weighted neighbourhood.

Similarly, the transformation which replaces the grey level value at a pixel by the minimum of the grey level value in its neighbourhood is known as the greyscale erosion operator as defined in Equation (4):

$$(f \ominus g)\ (z) = \min_{\mu \in R^2} \left[f(\mu) - g(\mu - z) \right] \tag{4}$$

Note that the dilation operator is extensive: $(f \oplus g)(z) \geq f(z)$ and the erosion operator is anti-extensive: $(f \ominus g)\ (z) \leq f(z)$.

Consider a greyscale signal *f(z)* and a structuring element *g* containing the origin. Kramer and Bruckner in [12], and then redefined by Schavemaker et al. in [13], used a flat or concave structuring element and the following discrete nonlinear filter to enhance the local contrast of *f(z)* by increasing its gradient as shown in Equation (5):

$$\Psi(f(z)) = \begin{cases} (f \oplus g)(z) & \text{if } f(z) \geq ((f \oplus g)(z) + (f \ominus g)(z))\,/\,2 \\ (f \ominus g)(z) & \text{if } f(z) < ((f \oplus g)(z) + (f \ominus g)(z))\,/\,2 \end{cases} \tag{5}$$

According to Equation (5), the output of the filter depends on the relative magnitude of the original signal *f(z)* as compared to the average of its eroded and dilated versions. If the original signal *f(z)* is greater than or equal to this average then the output of the filter Ψ follows the dilation of *f(z)*. If it is lower, then Ψ follows its erosion. The dilation is carried out by a flat or concave structuring element, and tends to be larger than the original signal close to the gradient. On the other hand, the erosion is lower than the original signal.

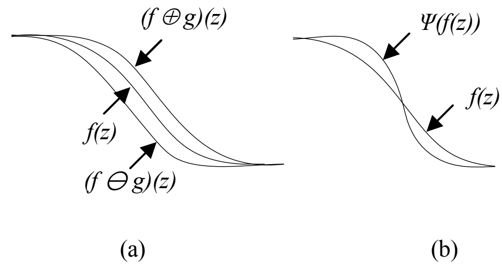

Figure 3 - (a) Dilation and erosion of a signal *f(z)* (b) Contrast enhancement of *f(z)* by switching between dilation and erosion using a sharpening filter Ψ.

Figure 3 shows that the output value of this filter switches between the value of the dilation of *f(z)* by *g(z)* and the value of its erosion by *g(z)*. This switch causes the gradient of the signal to increase, which leads to a contrast enhancement.

4. THE PROPOSED SHARPENING FILTER AND EXPERIMENTAL RESULTS

The sequence of applying the proposed filter will be explained before introducing the experimental results. First, the threshold decomposition method introduced in section 2.1 is applied to the low contrast medical image to produce a stack of binary images. At each level, a search is performed for the 16 possible edge directions as described in section 2.2. Binary morphological operations of dilation and erosion are used to increase the contrast in the region and direction of the detected edges with the aid of a flat structuring element [14]. A summation is applied over all levels in order to reconstruct the sharpened image. The nonlinear discrete filter is thus used to sharpen only at detected edges, rather than the whole image.

This section presents application results for the contrast enhancement of medical images. The performance of the proposed edge-detected morphological filter is compared with a number of contrast enhancement techniques including histogram equalization, modified high-pass filter [15], LUM filter [16], and quadratic weighted median filter (QWM) [17].

The proposed edge-detected morphological filter was tested on three medical images. As a first example, the *Chest X-ray* image shown in Figure 4(a) was used. Figures 4(b), 4(c), 4(d) and 4(e) show the contrast enhanced image after applying the histogram equalization filter, the modified high-pass filter, the LUM filter and the QWM filter respectively. Figure 4(f) shows the contrast enhanced image after applying the proposed edge-detected morphological filter. It can be seen that the latter gives the most distinct features.

As a second example, the *Hand X-ray* image shown in Figure 5(a) was used. This image demonstrates a fracture to the fifth metacarpal. Figures 5(b), 5(c), 5(d) and 5(e) show the contrast enhanced image after applying the histogram equalization filter, the modified high-pass filter, the LUM filter and the QWM filter respectively. Figure 5(f) shows the contrast enhanced image after applying the proposed edge-detected morphological filter. The fracture in this image appears clearer than the other images.

As a third example, the *Foot X-ray* image shown in Figure 6(a) was used. This image demonstrates a fracture to the base of the fifth metatarsal. Figures 6(b), 6(c), 6(d) and 6(e) show the contrast enhanced image after applying the histogram equalization filter, the modified high-pass filter, the LUM filter, and the quadratic QWM filter respectively. Figure 6(f) shows the contrast enhanced image after applying the proposed edge-detected morphological filter. The fracture in this image appears clearer than the other images.

From the figures of the filtered images, it is evident that the resulting images of the proposed edge-detected morphological filter are noticeably of higher contrast. Even the fractures and small details in the X-ray images have been enhanced.

Finally, the execution time of the proposed filter is introduced in Table 1. The proposed filter was performed on a Pentium IV processor running at 2.4 GHz with 512 MB RAM and using C++.

5. CONCLUSIONS

This paper introduced a new enhancement filter for digital medical images. In the proposed scheme, the edge detected guided morphological filter succeeded in enhancing low contrasted medical images. This was done by accurately detecting the positions of the edges through threshold decomposition. The detected edges were then sharpened by applying morphological filter using flat structuring elements. By utilising the detected edges, the scheme was capable to effectively sharpening fine details whilst retaining image integrity. The visual examples shown have demonstrated that the proposed method was significantly better than many other well-known sharpener-type filters in respect of edge and fine detail restoration.

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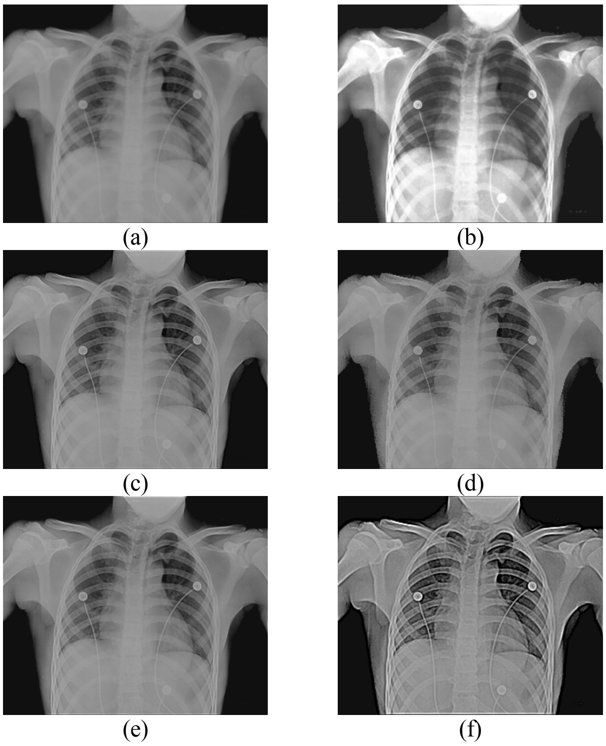

Figure 4 - (a) Low-contrast chest X-ray image (b) Histogram equalization (c) Modified high-pass (d) LUM (e) QWM (f) Proposed edge-detected morphological filter

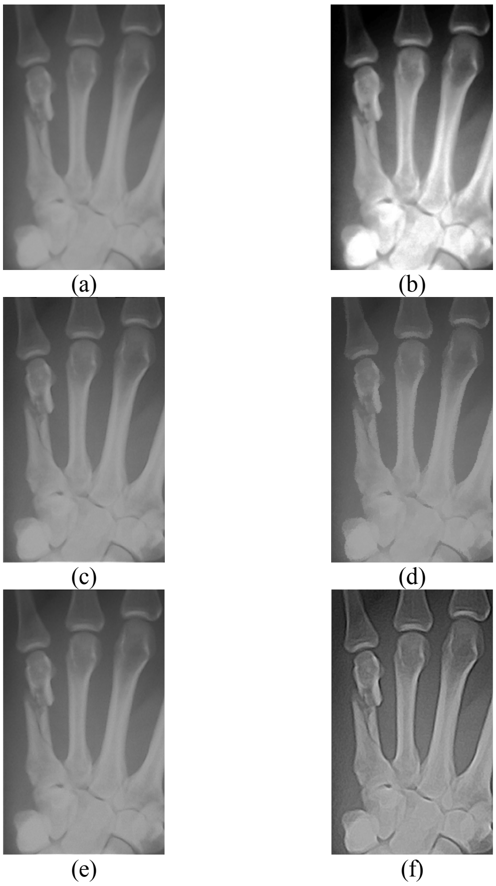

Figure 5 - (a) Low-contrast hand X-ray image (b) Histogram equalization (c) Modified high-pass (d) LUM (e) QWM (f) Proposed edge-detected morphological filter

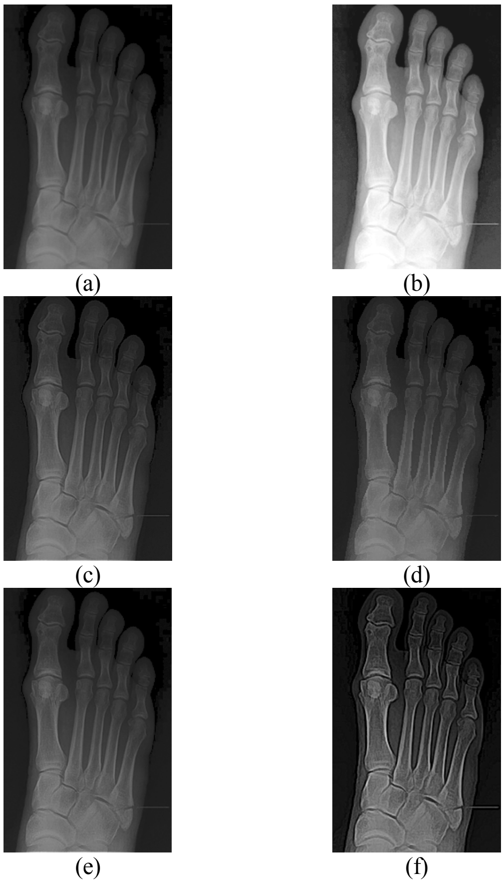

Figure 6 - (a) Low-contrast foot X-ray image (b) Histogram equalization (c) Modified high-pass (d) LUM (e) QWM (f) Proposed edge-detected morphological filter

Table 1 CPU execution time of the proposed filter applied on the examples used

	Image Size Width x Height (pixels)	CPU Time (seconds)
Chest X-ray	300 x 247	8.1
Hand X-ray	183 x 300	5.9
Foot X-ray	190 x 300	6.2