Computers in Biology and Medicine 37 (2007) 1455–1460

Computers in Biology and Medicine

www.intl.elsevierhealth.com/journals/cobm

A level crossing enhancement scheme for chest radiograph images

Nagesha*, G. Hemantha Kumar

Department of Studies in Computer Science, University of Mysore, Manasagangothri, Mysore 570006, India

Received 18 June 2006; received in revised form 22 December 2006; accepted 3 January 2007

Abstract

A new approach for contrast enhancement of chest radiograph image data is presented. Existing methods for image enhancement focus mainly on the properties of the image to be processed while excluding any consideration of the observer characteristics. In several applications, particularly in the medical imaging area, effective contrast enhancement for diagnostic purposes can be achieved by including certain basic human visual properties. In this paper we shall present a novel (recursive) algorithm that tailors the required amount of contrast enhancement based on a combination of the optimal phase representation and the theory of projection onto a convex set. Constraints of maximum bandwidth of the image data, appropriate knowledge of the amplitude value of the image data, heuristic limitations and level crossing measurements serve to impose additional information. So that, the enhanced image data may better converge to the good quality image.

Keywords: Level crossing; Image enhancement; Chest radiographs; Fourier transform; Histogram equalization

1. Introduction

Medical image enhancement is an important sub-problem of digital image processing, has been an active area of research for decades. Processing techniques concentrating on enhancement of contrast are of particular interest in the areas of chest radiography and mammography. In these areas constraints are inherently low due to small differences in the X-ray attenuation coefficients. In addition, the need for contrast enhancement also arises from the fact that current display devices such as CRT's are incapable of displaying as many different discernible levels of luminance as can be recorded in a digital image. Also, radiographs are generally viewed on a light-box. However, it is becoming increasingly common to digitize radiographs and view them on a high resolution monitor. Proper contrast conditions are very important when interpreting a radiograph. The contrast enhanced image can enhance or degrade the subtle details of radiographs.

Numerous image enhancement techniques have been developed and published in the literature [1,2]. They are generally classified into two categories: global techniques and adaptive techniques. For equalized global methods, one transform such as histogram equalization is applied to all the pixels of the input image. Adaptive methods generally involves an input to output mapping of the form $\tilde{I} = T[I, L]$ where L represents some local characteristics of the image I. Global methods may work well for some images. However, there are often more complex situations where an image may have enough global contrast with considerable low contrast details or the contrast is poor in some parts of the image but adequate in other parts of the image. In these cases adaptive contrast enhancement will provide significant advantages. On the other hand, [3] proposes a contrast enhancement method based on neural network. In this approach, the training data and decision rules would have significant influence on the processes result.

In this paper, we have presented a different approach by using level crossings of some predetermined amplitude levels, thus eliminating most of the amplitude portion of the image data. This method employs level crossing information, histogram equalization (HE) and phase information from Fourier transform of training set images. In order to apply additional a priori information about the amplitude levels of image data, we apply powerful mathematical theory projections onto convex sets (POCS). This additional information comprises of constraints

* Corresponding author. Tel.: +91 9448726790.
E-mail addresses: nagesh.bk@gmail.com (Nagesha), hemanth_kumar@lycos.com (G.H. Kumar).

0010-4825/$ - see front matter
doi:10.1016/j.compbiomed.2007.01.002

imposed on amplitudes of the image data, compliance with the information provided by level crossing measurements and other heuristic information. A detailed presentation of the proposed method is presented and an evaluation of its performance in the processing of several clinical chest images is given together with a comparison to histogram equalization.

In Section 2 of this paper, the proposed method for chest radiograph image enhancement is presented in detail. The convergence of the proposed method is described in Section 3. Section 4 describes the evaluation results and performance analysis followed by the conclusions in Section 5.

2. The level crossing based enhancement method

The performance of a contrast enhancement scheme can be significantly improved by incorporating characteristics of the human visual system. The property of the human visual system that will be of particular importance is that the human eye is more sensitive to random noise in smooth areas of the image than in "busy" areas where there are more details. The visibility of noise decreases monotonically with the increase in spatial activity which is defined as the rate of spatial changes in image intensity from one pixel to another. The enhancement from level crossing measurements adopted in order to increase the enhancement effect. This approach possesses several strong features. Prominent among these are: (1) a contrast level in the processed image judged to be adequate based on the observer characteristic is ensured; (2) ringing artefacts effectively eliminated and (3) any excessive enhancement of noise is avoided.

The basic idea behind the proposed method is to iterate between frequency and space domains by imposing appropriate constraints in each domain. The frequency domain constraint is derived from the physiological information of the previously diagnosed image data by extracting phase information. The spectral phase is extracted from the Fourier spectrum of image data. Spectral phase is coupled with magnitude of source image and inverse transformed to reconstruct the image thus enhancing the features of interest. This constraint provides some a priori knowledge about characteristics of the image data.

The second constraint limits amplitude levels of the image data with the support of predefined amplitude values (called levels). The level crossings are detected whenever the predefined amplitude levels are crossed by the original image amplitude values, thus eliminating most of the amplitude information of the image. The original image is enhanced from the information provided by the level crossings, along with phase information. Let us assume N_t levels $l_1 < l_2 < \cdots < l_{N_t}$ with the minimum amplitude value of image data less than l_1 and maximum value greater than l_{N_t} such that $l_{\text{lower}}(i, j, t) \leqslant I(i, j, t) \leqslant l_{\text{upper}}(i, j, t)$ where l_{lower} and l_{upper} bounds used for level crossing measurements at coordinate (i, j) of the source image with threshold level t.

The steps of the algorithm are as follows:

(1) Let image I^k be the result of the kth iteration.

(2) Impose the level crossing constraint by projecting I^{k+1} onto $I^{1\ k+1}$ via the operator P_1:

$$\tilde{I}^{k+1}(i, j, t) = \begin{cases} I^{k+1}(i, j, t), & l_{\text{lower}_l}(i, j, t) \leqslant I^{k+1}(i, j, t) \leqslant l_{\text{upper}}(i, j, t), \\ l_{\text{lower}_l}(i, j, t), & I^{k+1}(i, j, t) < l_{\text{upper}}(i, j, t), \\ l_{\text{upper}}(i, j, t), & I^{k+1}(i, j, t) > l_{\text{lower}}(i, j, t). \end{cases} \tag{1}$$

(3) Apply the projection operator $T_1 = 1 + \lambda_1(P_1 - 1)$ where λ_1 is the relaxation factor:

$$\begin{aligned} I^{1\ k+1}(i, j, t) &= T_1(\tilde{I}^{k+1}(i, j, t)) \\ &= \tilde{I}^{k+1}(i, j, t) + \lambda_1[\tilde{I}^{k+1}(i, j, t) \\ &\quad - I^{1\ k+1}(i, j, t)]. \end{aligned} \tag{2}$$

(4) Apply the histogram equalization to $I^{1\ k+1}$ with $(l_{\text{upper}}(i, j, t) - l_{\text{lower}}(i, j, t))$ grey level distribution. Resultant image is $I^{2\ k+1}$.

(5) Apply the projection operator $T_2 = 1 + \lambda_2(P_2 - 1)$ to $I''^{\ k+1}$:

$$\begin{aligned} I^{3\ k+1}(i, j, t) &= T_1(I^{2\ k+1}(i, j, t)) \\ &= I^{1\ k+1}(i, j, t) + \lambda_2[I^{2\ k+1}(i, j, t) \\ &\quad - I^{1\ k+1}(i, j, t)]. \end{aligned} \tag{3}$$

(6) Impose the phase constraint: let P_h denote the phase information of trained image set and M denote the magnitude of $I^{3\ k+1}$,

$$I^{4\ k+1} = IDFT(P_h, M). \tag{4}$$

(7) Apply the operator $T_3 = 1 + \lambda_3(P_3 - 1)$ to $I^{4\ k+1}$,

$$\begin{aligned} I^{5\ k+1}(i.j, t) &= T_3(I^{4\ k+1}(i, j, t)) \\ &= I^{3\ k+1}(i, j, t) + \lambda_2[I^{4\ k+1}(i, j, t) \\ &\quad - I^{3\ k+1}(i, j, t)]. \end{aligned} \tag{5}$$

If all the constraints at all points (i, j, t) are satisfied, stop the algorithm. Otherwise repeat steps (2)–(7).

3. Proof of convergence

The convergence of the proposed method is proved using the theory of POCS.

Theorem (*Youla and Webb [4], Vitsnvdel and Adam [5]*). *Define a Hilbert space H with elements $I_1, I_2, \ldots, I_n$ inner products $\langle\alpha, \beta\rangle$ and vector zero.*

Define convex sets $C_1, C_2, \ldots, C_n \in H$. Define C_0 as an intersection which is not empty set of $C_1, C_2, \ldots, C_n$:

$$C_0 = \bigcap_{0}^{n} C_i. \tag{6}$$