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Computer-assisted Diagnosis and Monitoring of Periodontal Diseases

C.C. Leung, F.H.Y. Chan
Department of Electrical & Electronic Engineering
The University of Hong Kong
Pokfulam Road, Hong Kong
ccleung@eee.hku.hk

K.Y. Zee
Faculty of Dentistry
The University of Hong Kong
Pokfulam Road
Hong Kong
kyzee@hkusub.hku.hk

P.C.K. Kwok
School of Science & Technology
The Open University of Hong Kong
30 Good Shepherd Street
Kowloon, Hong Kong
ckkwok@ouhk.edu.hk

Abstract

In the diagnosis of periodontal diseases, Digital Subtraction Radiography (DSR) is often used. A pair of dental radiographs is taken a few months apart. The difference between the two radiographs can be used as a basis for diagnosis. Even though the radiographs are in digital form, the alignment process to ensure an exact match between the two radiographs is done manually. Furthermore, there would be mismatch in exposure that affects the substraction and hence diagnosis results. The mismatch is simply ignored in the manual process.

We propose a DSR system with computer-assisted alignment; and exposure compensation. In this paper, we focus on the exposure compensation technique that is based on the modified Generalized Fuzzy Operator and least squares method.

1 Introduction

Digital Subtraction Radiography (DSR) is a powerful tool for diagnosis of periodontal disease [1-3]. Dental radiographs (Figure 1) are taken typically at 6-month intervals. A pair of radiographs are superimposed upon each other and subtracted. A region of interest (ROI) is identified by the dentist and the difference in pixel values in the ROI is a useful indicator for the diagnosis and monitoring of periodontal diseases.

The radiographs are digitized and presented on the screen. The alignment is then performed manually and subtraction is performed by software. There are a number of problems with this process. (a) The geometry between the two radiographs may be different because the x-ray film is subject to bending when it is mounted in the patient's oral cavity. (b) In spite of the procedures used in controlling the exposure time, current and voltage setting of the x-rays machine, and by careful film processing with quality control of the chemicals, differences in contrast/brightness between a pair of radiographs, cannot be totally eliminated. Since the accuracy of the diagnosis is based on the differences between the two radiographs, it is important that the two images are compensated in the exposure factors.

We have constructed a semi-automatic system to compensate for the above two problems. The processing schematic of the system is shown in Figure 2. In this paper, the first image of the pair is called the reference image. The second of the pair is called the subsequent image. Exposure compensation, i.e., contract normalization is performed on the subsequent image. Afterwards, it is translated to align with the reference image. Subtraction then takes place, to be followed by counting of the pixels and diagnosis. In this paper, we present the solution to the exposure compensation problem.

2 Prior Work

Non-parametric contrast correction methods have been reported in [4-5]. They are based on a cumulative density function (CDF). It is a mapping technique in which the histograms of the pixel values of the reference and subsequent images are compared. Several methods based either on a linear least squares approximation or on CDF, were reviewed in [6]. The non-parametric algorithm based on CDF is proved to be constantly and statistically significantly better than the ones based on linear approximation. The use of reference structures on the radiographs did not further improve the ability of the normalization methods to correct gray level mismatches between radiographic pairs. However, the accuracy of CDF depends on the number of selected region, the size of each region, and the gray levels mapping in the selected regions. In the presence of non-uniform contrast/brightness differences between the radiographs, the mapping result will be unsatisfactory.

Chen et al [12,15] proposed the Generalized Fuzzy Operator (GFO) for edge detection and contrast enhancement. The generalized fuzzy set can separate regions automatically based on one parameter and the Sine function.

3 The Proposed Algorithm

We propose a new method based on modify Generalized Fuzzy Operator (mGFO) together with the Least Squares method (LS) to correct the brightness/contrast in the presence of non-uniform differences. Three different regions are selected from the image. The first region (I) is where we would expect to have a change in brightness/contrast in the scene (highlighted in Figure 1). The second region (II) is where we do not expect a change. The third region (III) is selected from a neighborhood where the gray level should be as low as possible but not equal to zero. These three regions in the reference image are matched with the same regions in the subsequent image using the mGFO with LS.

The new approach includes two algorithms: mGFO and LS. mGFO is used to decompose the subsequent image based on the fuzzy set with parameters obtained from the LS. The decomposed image is then re-mapped into a new subsequent image. Details are shown below.

3.1 Least Squares method using Normalized Local Contrast

Contrast is the difference in luminance between objects and background. According to Weber's Law [10], the contrast C_i is defined as

$$C_i = \frac{|B_o - B_b|}{B_b} \quad (1)$$

where B_o is the brightness stimuli of the object and B_b is the object background. The contrast can be normalized by

$$C_i' = \frac{(C_i - \mu_{c_i}(x,y))}{\sigma_{c_i}(x,y)} \quad (2)$$

where C_i denotes the corrected brightness/contrast in the selected area i of the image, μ_{c_i} represents the mean of the pixel values in the area, and σ_{c_i} is the smoothing function (filter function). Next, we redefine the smoothing function σ_{c_i} based on the pixel histogram of the selected regions.

Let S_i, $i = 0,1, ...,k$ be the pixel sequence in a region of the reference image, and S_j, $j= 0,1, ...,k$ is the sequence in the same region of the subsequent image. The brightness/contrast error is defined by the difference between the two sequences S_i and S_j:

$$\varepsilon_k = S_i - S_j = S_i + \sum_{j=1}^{p} \overset{o}{a}_j S_{k-j} \quad (3)$$

where $\overset{o}{a}_j$ denotes the estimated pixel value that is the difference between the normal and abnormal regions. Next, we apply the LS method [12],

$$\underset{\overset{o}{a}_j}{Min}\, E\{\varepsilon_k^2\} = \underset{\overset{o}{a}_j}{Min}\, E\left\{\left(S_i + \sum_{j=1}^{p} \overset{o}{a}_j S_{k-j}\right)^2\right\} \quad (4)$$

by differentiating $E\{\varepsilon_k^2\}$ with respect to a_1 and a_2,

$$\frac{\partial E\{\varepsilon_k^2\}}{\partial \overset{o}{a}_j} = 0 \quad (5)$$

where $j=1,2$.

The estimated error values from equation 5 can be used as smoothing function to correct the brightness/contrast in the subsequent image. Thus,

$$\sigma_{c_1} = a_1 \text{ and } \sigma_{c_2} = a_2$$

3.2 Modified Generalized Fuzzy Operator

The GFO [11] is defined as

$$GFO[\mu_s(x)] = \begin{cases} \sqrt[\beta]{1-[1+\mu_s(x)]^\beta}, & -1 \le \mu_s < 0 \\ [\mu_s(x)]^\beta, & 0 \le \mu_s < \gamma \\ \sqrt[\beta]{1-\alpha[1-\mu_s(x)]^\beta}, & \gamma \le \mu_s(x) \le 1 \end{cases} \quad (6)$$

where $x \in R$, and $\mu_s(x) \in [-1,1]$ is called the Generalized Membership Function of Generalized fuzzy set ς in the region $\Re$. Then, we use a Sine function to map the reference image $X(i,j)$ into a fuzzy set $P_k(i,j)$:

$$P_k(i,j) = \sin\left\{\frac{\pi}{2}\left(1 - \frac{X_k(i,j) - X_{\min}}{D}\right)\right\} \quad (7)$$

where $\frac{X_{\max} - X_{\min}}{2} \le D$ and $k=1,2,...,5$.

Then, $P_k \in [-1,1]$ is mapped to the new fuzzy set P' as shown in the following equation. Let $k=1$,

$$P'(i,j) = \begin{cases} a \times \left\{\left\|\frac{P(i,j) - P_{k+4}}{\sigma_{c_1}}\right\|\right\}, & P_k < P(i,j) < P_{k+1} \\ a \times \left\{\left\|\frac{P(i,j) - P_{k+4}}{\sigma_{c_2}}\right\|\right\}, & P_{k+2} < P(i,j) < P_{k+3} \\ [P(i,j)], & others \end{cases} \quad (8)$$

The three parts in equation 8 corresponds to the regions I, II, and III described above, in that order.

By using $\beta=2$ and $a=1$, the newer image $X'(i,j)$ is

$$X'(i,j) = X_{\min} + D\left\{1 - \left[\frac{\sin^{-1}(P(i,j))}{\frac{\pi}{2}}\right]\right\} \quad (9)$$

The brightness/contrast in the subsequent image can be corrected by equation 8 based on the smoothing function σ_{c_1} and σ_{c_2}.

4. Results and Discussions

The method has been tested on a variety of dental image sequences. A typical example is present here.

In DSR, a typical threshold to use would be ±7 [6]. That is to say, the number of pixels exceedings 7 expressed as a percentage of the total number of pixels in the ROI is a parameter for the basis for diagnosis. Thus, a brightness/contract normalization method for DSR must produce a compensation accuracy to better than ±7, in order for the system to be usable. In the following, we make a comparison between CDF and the proposed method. The test images presented here are taken one in the same X-ray session. There should not be any changes to the patient's condition. So in the ideal case, there should not be any differences between the two radiographs. The subtracted image should be zero everywhere. In practice, the two images are not exactly identical because they underwent different film exposure and processing.

Figure 1 shows the reference image obtained by digitized at 600dpi. For the sake of comparison, the subsequent image has a large contract difference with the reference, with difference of more than 7 for all pixels.

Figure 3 and 4 are the histograms of the pixel values for the case of CDF and mGFO/LS respectively. In the case of CDF, 47.2% of the pixels have been corrected to have a difference of less than 7. On the other hand, 72.2% of the pixels have been corrected for the case of mGFO/LS. The scenario here is an extreme case. In a typical dental radiograph pairs, the differences are much less to start with, so that the proposed method can compensate for the differences very effectively.

When using CDF method, it has been shown that successful results in the correction of contrast/brightness could be obtained if the differences were uniform between the two images [14]. However, it does not work well when there are localized regions with differences in the contrast/brightness.

Correction of brightness/contrast using the proposed algorithm is based on the fuzzy sets P_k. The conditions of fuzzy set are related to the histogram of the selection regions. A region with differences in brightness/contrast is selected as the fuzzy sets P_1 in the reference image and P_2 in the subsequent image while another region without changes is chosen as P_3. A region with lowest gray level but not equals to zero is chosen as P_4 and P_5 in the reference and subsequent image, respectively. Correction of brightness/contrast is processed using these fuzzy sets within the mGFO to obtain the new fuzzy set $P^{'}$. Background noise was removed by using the smoothing function σ_{ci} obtained from LS. No change of the object is obtained by the term $[P(i,j)]$ within the new fuzzy set $P^{'}$.

5 Conclusion

The modified Generalized Fuzzy Operator with Least Square method was presented. It is a simple, effective and efficient method for correction of brightness/contrast in a localized region. This algorithm has been applied to the digital subtraction radiography very effectively.

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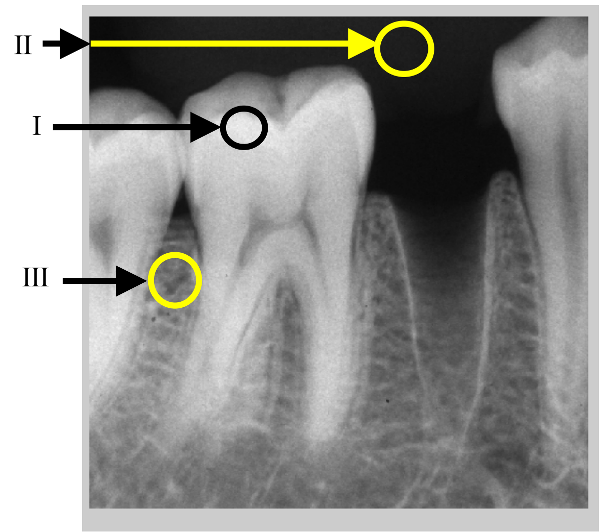

Figure 1. A typical dental radiograph showing a molar and the surrounding tissues.

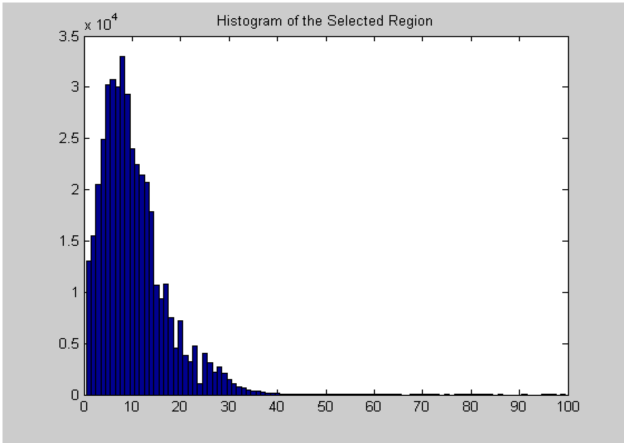

Figure 3. Histogram of the ROI with exposure compensation by CDF.

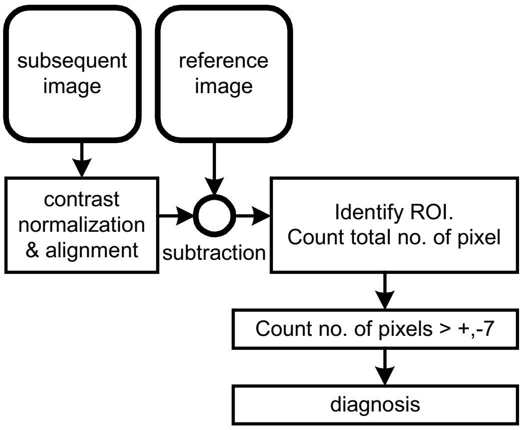

Figure 2. Processing Schematic for DSR

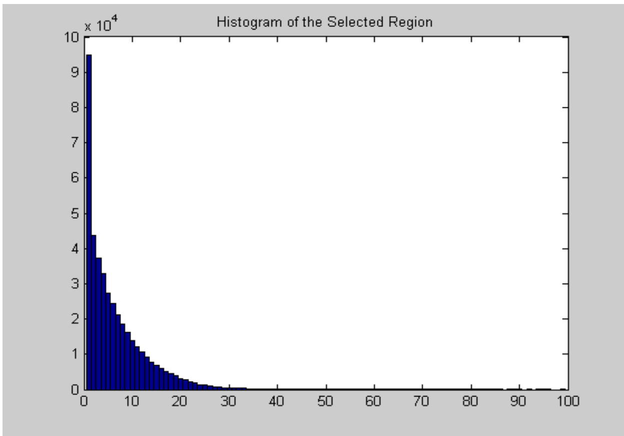

Figure 4. Histogram of the ROI with exposure compensation by mGFO.