GAUSS FILTERING FOR DETERMINING REGION OF INTEREST ON MEDICAL IMAGES

MEDİKAL GÖRÜNTÜLERDE İLGİ ALANI TESPİTİ İÇİN GAUSS FİLTRELEMESİ

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ABSTRACT: Medical imaging techniques; are commonly used techniques for disease diagnosis, health monitoring and treatment. The quality of the medical image directly affects the quality of diagnosis and treatment. Due to the importance of the medical image, storage and transmission require extra safety precautions. Storing images by compression may cause noise in the image. A loss of data during transmission of the image may cause image distortion. If a patient's medical image is mixed with another patient, it can have irreversible vital consequences. The best ways to deal with these problems are segmentation of the medical image and watermarking. In this study, a simple and fast segmentation algorithm is proposed which is based on Gaussian smoothing and block comparison methods and runs on high resolution medical images. With the proposed algorithm, the medical image is divided into Region Of Interest (ROI) and Region Of Non-Interest (RONI). Thus, ROI can be preserved in image compression and transmission or various information can be watermarked into these regions.

Key words: Medical image, watermarking, segmentation, Gauss.

ÖZET: Medikal görüntüleme teknikleri; hastalık teşhisi, sağlık durumunun izlenmesi ve tedavi için yaygın olarak kullanılan tekniklerdir. Medikal görüntünün kalitesi, teşhis ve tedavi kalitesini doğrudan etkiler. Medikal görüntünün öneminden dolayı saklanması ve iletimi ekstra güvenlik tedbirleri gerektirir. Görüntülerin sıkıştırılarak saklanması, görüntüde gürültüye sebep olabilir. Görüntünün iletimi sırasında oluşacak bir veri kaybı, görüntüde bozulmalara neden olabilir. Bir hastanın medikal görüntüsü başka bir hasta ile karışırsa, geri dönülmez hayati sonuçları olabilir. Bu problemlerle başa çıkmanın en iyi yolları medikal görüntünün segmentasyonu ve damgalamadır. Bu çalışmada, Gauss yumuşatması ve blok karşılaştırma tabanlı ve yüksek çözünürlüklü medikal görüntülerde çalışabilecek basit ve hızlı bir segmentasyon algoritması önerilmiştir. Önerilen algoritma ile medikal görüntü ilgi bölgesi (ROI) ve ilgi olmayan bölgelere (RONI) ayrılmıştır. Böylece görüntü sıkıştırmada ve iletimde ROI bölgesi korunabilir veya bu bölgelere çeşitli bilgiler damgalanabilir.

Anahtar sözcükler: Medikal görüntü, damgalama, segmentasyon, Gauss

INTRODUCTION

The process of creating visual representations of the inner part of the body for clinical analysis and medical intervention is called medical imaging. Medical imaging is very important for disease diagnosis, treatment and surgical planning (Kaur and Goyal, 2014). Commonly used medical imaging methods are Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Ultrasound images (US) and Poistron Emission Tomography (PET) (Sudha et al., 2019). The idea of using image processing technologies on medical images is introduced in the 1990s. Before the 1990s, medical images were physically printed and stored in hospital archives. Medical images stored digitally in hospital databases after these years until today. In addition to medical images, patient information, disease history, diagnosis, treating doctors and treatment information are also stored in the database. Thus, doctors are able to monitor the treatment process more easily after the examination. In addition, it became easy to comment on the relapse of the disease or its association with other diseases.

The storage of medical images in digital environment brings some difficulties such as security and storage space cost as well as the convenience. For example, a 12-bit medical X-Ray image with a resolution of 2048x2560 pixels has a file size of 10,485,760 bytes. Similarly, a typical 16-bit mammography image of 4500x4500 pixels produces a 40,500,000 bytes (40 megabytes) file. According to statistics, the need for medical storage in the world increases by more than 11 percent each year (Janaki and Tamilarasi, 2011). The rapid increase in storage requirements has led to the search for new compression techniques. The biggest challenge to compression techniques is the ever-changing medical imaging techniques. It is difficult to compress a medical image because a noise and loss of quality during image compression may also change the diagnosis (Kaur & Goyal, 2014).

The databases where medical images are stored were initially accessible only in hospitals. However, with the developing technology, these databases are connected to the internet for patients' access. Allowing external access to the database brings out the problem of preserving the integrity of medical images. The most common technique used to preserve the integrity of the medical image is embedding an integrity watermark into the medical image. Another security concern is the unauthorized use of the medical image in an open access database which is preventing by embedding a copyright watermark into the medical image (Wakatani, 2002). Another problem that may occur in medical image databases is the possibility of mismatching of patients with medical images. Such an error can lead to fatal consequences. The techniques developed to prevent this condition are generally based on embedding patient information in the medical image as a watermark. These all watermark types for medical images are named as Medical Image Watermark (MIW). Due to the precise nature of the medical image, it is envisaged that the added watermarks will not alter the perceptual structure of the image. A deterioration caused by MIW may cause misdiagnosis or malpractice (Kundu and Das, 2010).

Image segmentation techniques are used to prevent distortion of the medical image in these procedures. Image segmentation is the process of splitting an image into several sections. The important part of the medical image for diagnosis is marked by the doctor as shown in the Figure 1 before being stored in the database (Sudha et al., 2019).

Figure 1. Region Of Interest And Region Of Non-Interest (Agung vd. 2012)

The significant part is called ROI and the unimportant part is called RONI (Kaur & Goyal, 2014). Any loss in RONI does not affect the treatment and diagnosis process. However, the segmentation technique varies for each medical application. For example, the segmentation of the brain image is different from the segmentation of the heart image. During the transmission, compression or watermarking of the medical image, distortions in the image can be prevented by considering ROI and RONI (Maulik, 2009). The best approach here is to apply compression and watermarking only in the RONI.

In medical images, segmentation can be done automatically by a software or manually by the doctor. However, there is no universal algorithm for segmenting each medical image. Automatic segmentation of medical images is difficult due to the complexity of the images (Manikpuri and Kamargaonkar, 2017).

METHOD

ROI and RONI segmentation of the medical image is performed in this study. It is assumed that a watermark containing the patient, doctor, diagnostic and treatment information will be embedded in the medical image. The image is first divided into equal sized blocks and a copy of each block is created. Gauss smoothing is applied to each of the replicated blocks with a predetermined standard deviation to determine whether each block has any detail. The main purpose of Gaussian smoothing is to blur the block by eliminating noise in the block. For a one-dimensional *x* series, the Gaussian function is the same in the equation 1.

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}} \tag{1}$$

σ shows the standard deviation of the distribution. The 2D Gauss function is used when working on images. Gaussian smoothing for an image with dimensions x and y is shown in the equation 2.

$$G(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

Structured Similarity Index Measure (SSIM) is used to measure the structural change in the blocks after applying Gauss smoothing. SSIM is a difference measure that measures the change in three facts which are brightness, contrast and structural changes. SSIM is calculated as in equation 3 for the images I and I'.

$$SSIM(I,I') = l(I,I')^{\alpha}.c(I,I')^{\beta}.s(I,I')^{\gamma} \tag{3}$$

l, c and s in the equation show brightness, contrast and structural difference, respectively, and are calculated as in the equations 4a, 4b and 4c.

$$l(C,C') = \left(\frac{2\mu_C\mu_{C'} + k_1}{\mu_C{}^2 + \mu_{C'}{}^2 + k_1}\right) \tag{4a}$$

$$c(C,C') = \left(\frac{2\sigma_C\sigma_{C'} + k_2}{\sigma_C{}^2 + \sigma_{C'}{}^2 + k_2}\right) \tag{4b}$$

$$s(C,C') = \left(\frac{2\sigma_{CC'} + k_3}{\sigma_C + \sigma_{C'} + k_3}\right) \tag{4c}$$

The proposed algorithm is explained step by step below.

1. Import mxn pixels medical image as I (equation 5).

$$I = \{x_{ij} | 1 \le i < m, 1 \le j < n\} \tag{5}$$

2. Read pixelsize p of each block and watermark data size sd. These data can manually preform by user or automatically by a software which is priorly trained by several similar processes.

3. Calculate needed block count (nbc) with equation 6.

$$nbc = \left(\frac{s_d}{p^2}\right) \tag{6}$$

4. Divide image I into B blocks sized m/p rows and n/p columns as in equation 7.

$$I_{(i,j)} = \sum_{i=1}^{\frac{m}{p}} \sum_{j=1}^{\frac{n}{p}} B_{(i,j)} \tag{7}$$

5. Create a copy of each block with equation 8.

$$I'(i,j) = I(i,j), i \in \left\{1,2,\ldots,\frac{m}{p}\right\}, j \in \left\{1,2,\ldots,\frac{n}{p}\right\} \tag{8}$$

6. Apply Gauss filter to each copy with given standart deviantion σ as in equation 9.

$$I'\left(\frac{m}{p},\frac{n}{p}\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(\frac{m}{p})^2+(\frac{n}{p})^2}{2\sigma^2}} \tag{9}$$

7. Create SSIM Result Matrix consisting of m/p rows and n/p columns comparing each original block and filtered blocks. Each cell of the matrix is equal to zero (Equation 10).

$$SSIMResult(i,j) = 0, i \in \left\{1,2,\dots,\frac{m}{p}\right\}, j \in \left\{1,2,\dots,\frac{n}{p}\right\} \tag{10}$$

8. Calculate SSIM of each block with corresponding copy which is smoothed by 2D Gauss filtering (Equation 11).

$$SSIMResult(i,j) = SSIM(I(i,j), I'(i,j)) \tag{11}$$

9. Scan each line of SSIMResult matrix to find maximums of each line. Sync the cell or cells to "1" which contains the maximum value of the line and sync other cells to "0".

10. Scan each column of SSIMResult matrix to find maximums of each column. Sync the cell or cells to "1" which contains the maximum value of the column.

11. Calculate mean of each four cells and generate a new neighborhood mean matrix which is quarter size of SSIM matrix.

12. Calculate mean of each four cells and generate a new neighborhood mean matrix which is one-sixteen size of SSIM matrix. Last two steps are shown in Figure 2 as an example.

$$\begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \xrightarrow[\text{Step 11}]{\text{First mean matrix}} \begin{bmatrix} 0.25 & 0.5 \\ 0.25 & 0 \end{bmatrix} \xrightarrow[\text{Step 12}]{\text{Second mean matrix}} \begin{bmatrix} 0.25 \end{bmatrix}$$

Figure 2. Step 11 and 12 for a sample 8x8 SSIMResult matrix

13. Calculate necessary block count for watermarking on second mean matrix with equation 12.

$$nbc = ceil\left(\frac{nbc}{16}\right) \tag{12}$$

14. Point each cell referring to 16 blocks of image *I* as RONI which include the biggest number in mean matrix

EXPERIMENTAL RESULTS

The proposed algorithm is tested on two different features of the medical image shown in the Figure 3. The Test1 image is an Ultrasound image with a resolution of 800x600 pixels. Test2 image is an X-ray image with a resolution of 600x400 pixels. These images are selected to be extremely small in size to test the success of the method. Medical images used for testing are selected from the sample images presented on the web site of RadmediX Inc. and from Clarkes3Dultrasound.com.

(a) (b)

Figure 3. Images Test1 (a) and Test2 (b)

It is assumed that watermarks sized 1KB, 2KB, 4KB, 8KB and 16KB will be embedded in the selected medical images with small pixel density. Since one alphanumeric character is encoded in one byte in ASCII encoding, the 16KB watermark may contaion a text with more than 16000 characters. A text of this length is more than enough to carry all the information such as patient, doctor, diagnosis and treatment. Copyright information may also be included in this text. In addition, the ROI regions obtained by running the method at different block sizes are compared. The results are shown in the Table 1 and Table 2.

Table 1. Results for Test1

	Watermark size:1KB	Watermark size:2KB	Watermark size:4KB	Watermark size:8KB	Watermark size:16KB
Block size:8					
Block size:16					

Table 2. Results for Test2

	Watermark size:1KB	Watermark size:2KB	Watermark size:4KB	Watermark size:8KB	Watermark size:16KB
Block size:8					
Block size:16					

The shaded areas in Table 1 and Table 2 show the RONI detected by the proposed algorithm. This area is selected according to the predefined watermark size. This is based on the Least Significant Bit (LSB) algorithm. According LSB, one pixel of the image is used for each watermark bit. Taking into account that the pixel sizes of the test1 and test2 images are small, the actual size of the medical images may be capable of carrying much more data with the proposed algorithm.

To interpret the performance of the algorithm, runtime versus watermark size graph is given in Figure 4 while the block size is constant.

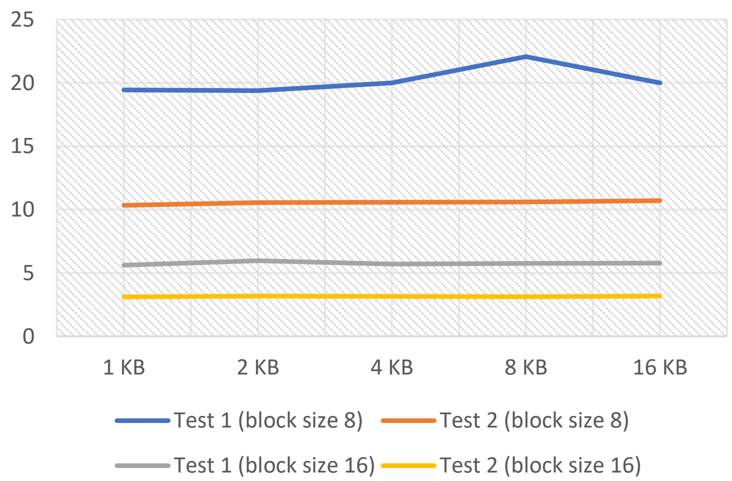

Figure 4. Runtime Versus Watermark Size Graph

As is evident from Figure 4, the watermark size does not significantly alter the algorithm time. The factor affecting the algorithm time is the block size.

In this study, an automatic ROI detection method which works fast and has low process complexity is proposed. In future studies, it is aimed to determine the block size of the proposed method by considering the watermark size and medical image characteristics in advance.

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