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AUTOMATIC COLON SEGMENTATION USING CELLULAR NEURAL NETWORK FOR THE DETECTION OF COLORECTAL POLYPS

Niyazi KILIC[1*] Onur OSMAN[2] Osman N. UCAN[1] Kemal DEMIREL[3]

[1]Istanbul University, Engineering Faculty, Electrical and Electronics Eng. Dept., 34320, Avcilar, Istanbul, Turkey
{niyazik@istanbul.edu.tr}

[2]Istanbul Commerce University, 34378, Eminonu, Istanbul, Turkey

[3]Istanbul University , Cerrahpasa Faculty of Medicine,Radiology Dept., Cerrahpasa, Istanbul, Turkey

ABSTRACT

In this paper, an automatic colon segmentation method for Computed Tomography (CT) colonography is presented. Colon segmentation is considered in order to prevent the time consumption while searching polyps out of the colon region and reduce radiologists' interpretation time. The proposed method is the combination of pre-processing and Cellular Neural Networks (CNN). Also recurrent perceptron learning algorithm (RPLA) is used for CNN training. Original CT images are passed through a threshold and then CNN is used to erase unrelated small objects and smooth sharp corners. It is expected automatic colon segmentation will improve the radiologists' diagnostic performance.

Keywords: *Virtual colonoscopy, Segmentation, Colorectal polyp, Cellular Neural Network*

1. INTRODUCTION

Colon cancer is still an important health problem that causes serious morbidity and mortality. It is the second leading cause of cancer death in the developed nations [1]. Most colon cancers originate from pre-existing adenomatous polyps, which take 5 to 15 years for malignant transformation. Early detection and removal of the polyps dramatically reduce the risk of death. Current colon cancer screening techniques have been shown to decrease in the morbidity and mortality associated with colon cancer by allowing detection and leading to removal of premalignant adenomatous polyps. [2-3]. Colonoscopy is known to be the gold standart procedure for screening the colon. But diminutive lesions can still be missed by colonoscopy through observer error or due to the polyp's being situated in a blind area [4]. Virtual colonoscopy can study the colon above an

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obstructive lesion and can analyze the margins of the haustrations in both an antegrade and retrograde manner to reveal lesions that may be missed at conventional colonoscopy [5-6]. Therefore, only suspicious findings uncovered using non-invasive virtual colonoscopy screening would need to be re-examined by invasive colonoscopy follow-up. As a screening modality, virtual colonoscopy has another advantage of making use of computer-aided detection (CAD) techniques to examine the internal tissue image textures beyond the inner surface of the colon. A CAD scheme that automatically detects potential polyp candidates could substantially reduce the radiologists' interpretation time and improve their diagnostic performance with reduced false positives [7-9]. Figure 1 shows some typical polyp examples in CT colonography.

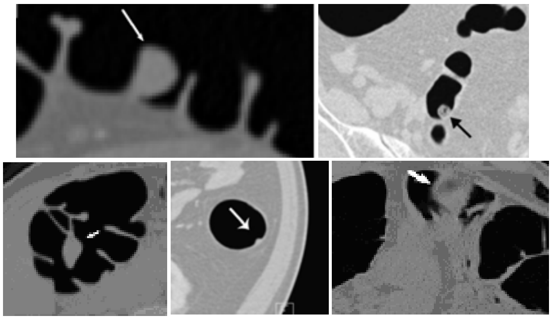

Figure 1. Polyp examples in CT colonography.

Cellular Neural Networks (CNNs) model has been defined firstly in 1988 by Chua [10]. The basic circuit unit of cellular neural networks is called a cell. It contains linear and non-linear circuit elements. There are many well-known applications of CNN like image processing, motion detection, pattern recognition [11].

In this paper, an automatic colon segmentation approach in CT colonography for detection of colonic polyps has been presented. Cellular Neural Network (CNN) is used for segmentation process.

2. MATERIALS AND METHODS

In this paper, colon segmentation is considered in order to prevent the time consumption while searching polyps out of the colon region in the CT image. CNN is used for this process to search in the colon region since colorectal polyps occurs inside the colon region in the CT.

2.1. Input Dataset

12 patients (4 men, 8 women; age range 27-83 years) were enrolled in this study. All scans were performed with a 16 detector CT scanner. The scanning parameters were 120kV, 50mAs, 0.75mm collimation; images were reconstructed as 1mm thick slices of 512x512 array size, 0.6 mm reconstruction interval; 0.5 second gantry rotation time and the entire region of abdomen and pelvis could be imaged during 12 second breath hold. Each slice consists of unit elements called as voxels having values due to the thickness of the slice.

2.2. Cellular Neural Networks

The Cellular Neural Networks (CNN), introduced in [10], have a suitable structure for image processing.

If $C_{i,j}$ represents the cell located in the (i, j)-th position of a 2D $M \times N$ image and $N_{i,j}$ represents the r-neighborhood of the cell $C_{i,j}$ and is defined by

$$N_{i,j} = \left\{ \begin{matrix} C_{l,m} \mid \max(|l-i|,|m-j|) \le r; \\ 1 \le l \le M,\ 1 \le m \le N \end{matrix} \right\} \quad (1)$$

can be written.

Where r is a positive integer. The pixel intensity (the state) $x_t(i, j)$ at this location can be described by the following discrete state equations:

$$x_{t+1}(i,j) = \sum_{C_{l,m} \in N_{i,j}} A_{l,m} \times y_t(i+l, j+m) + \sum_{C_{l,m} \in N_{i,j}} B_{l,m} \times u(i+l, j+m) + I \quad (2a)$$

$$y_t(i,j) = 0.5 \times \{ |x_t(i,j)+1| - |x_t(i,j)-1| \} \quad (2b)$$

Here, $u(i,j)$ is the input, $x_t(i,j)$ and $y_t(i,j)$ are the state and the output of the cell $C_{i,j}$ at the t^{th} instant, respectively. $A_{l,m}$ and $B_{l,m}$ are the inputs at the *l, m*th neighborhood of the feedback and control templates *A* and *B*, centered at the location *(i,j)*. *I* is a constant bias parameter. The initial state is assumed to have magnitudes equal to 1. Note that $|y_t(i,j)| = 1$ for all $t \geq 0$.

2.3. Segmentation Algorithm

In this study, we segment the colon region from the CT colonography image by applying a hard decision process for gray-level thresholding (-800HU). Hounsfield Unit (HU) is a unit of x-ray attenuation used for CT scans, each voxel being assigned a value on a scale where air is -1000, water is 0, and compact bone is +1000 [12].The adjacent voxels having HU values higher than -800HU define the colonic wall. Tresholding process can be written as following:

if C(x,y,z) > -800 then
C(x,y,z) is a colon region
else
C(x,y,z) is not a colon region
end

where *C(x,y,z)* is the CT image

Then CNN is used to erase small objects and smooth sharp corners. Since the initial state values of CNNs are bounded between -1 and +1, the CT image intensity values are normalized before use.

2.3.1. Removal of the Background.

To segment the background, region growing method is used. This well-known algorithm is described in many articles [13-14]. Removal of the background is performed automatically using the region growing method with eight different seed points located in the corners of the volume that correspond to the air surrounding of the patient. In this section, we changed black background of CT image to white since removal of the background is necessary in order to obtain a better result in CNN training phase.

2.3.2 CNN Application to CT Colonography Images

For the cellular neural networks, there is not an analytically developed learning algorithm to perform any kind of processing. In this study, Recurrent Perceptron Learning Algorithm (RPLA) is used for CNN training [15].

RPLA is a learning algorithm. The goal of this algorithm is to obtain the weighting coefficients and the threshold value that will perform the desired image processing procedure. In this study, desired image is constructed from the healthy person colon region image. In this synthetic colon, all polyp candidates are inside the border of the colon. CNN input image and desired image which are used in the training are shown in figure 2a and 2b.

a) b)

Figure 2. a) CNN input image
b) Desired image

The error function E[w] is the measure of the difference between the original output (steady-state output) value and the desired output value. The goal of the RPLA algorithm is to obtain the w weighting coefficients that are suppose to minimize this error function. *A*, *B* templates and *I* bias are obtained from the learning process.

CNN image processing includes two steps. The first step involves the learning step. At this step, the input object is the CT slices which have been exposed to tresholding process whereas the output object is the desired (colon regions in CT slices) image. Here, initial value $x(0)$ is chosen 1 (one). This step is where the weighting coefficients are determined. The *A*, *B* and *I* values are found as following:

$$A = \begin{pmatrix} 0.7594 & 1.5188 & 1.1391 \\ 0.9113 & 1.4428 & 0.9113 \\ 1.1391 & 1.5188 & 0.7594 \end{pmatrix},$$

$$B = \begin{pmatrix} 1.5188 & 2.2781 & 3.0375 \\ 3.7969 & 0.8353 & 3.7969 \\ 3.0375 & 2.2781 & 1.5188 \end{pmatrix},$$

$$I = 0.8353,$$

The following step involves the test where another CT slice image is used as the input value to the system. At this step, the weighting coefficients (determined at the previous step) are used to obtain the output image.

The images obtained by CT colonography are segmented by CNN and the results are shown in the next section.

3. RESULTS

CNN algorithm is applied to the images obtained from virtual colonoscopy. Figure 3 shows the segmentation results obtained during the test phase of CNN. Regions of colon in CT colonography automatically extracted from other parts using CNN are also shown in this figure. It is also clear that automatic segmentation minimizes subjectivity. Moreover, computer aided detection (CAD) systems for detecting colorectal polyps will not be employed in the whole CT slice, but only employed in segmented colon region. Therefore performance of CAD systems will increase.

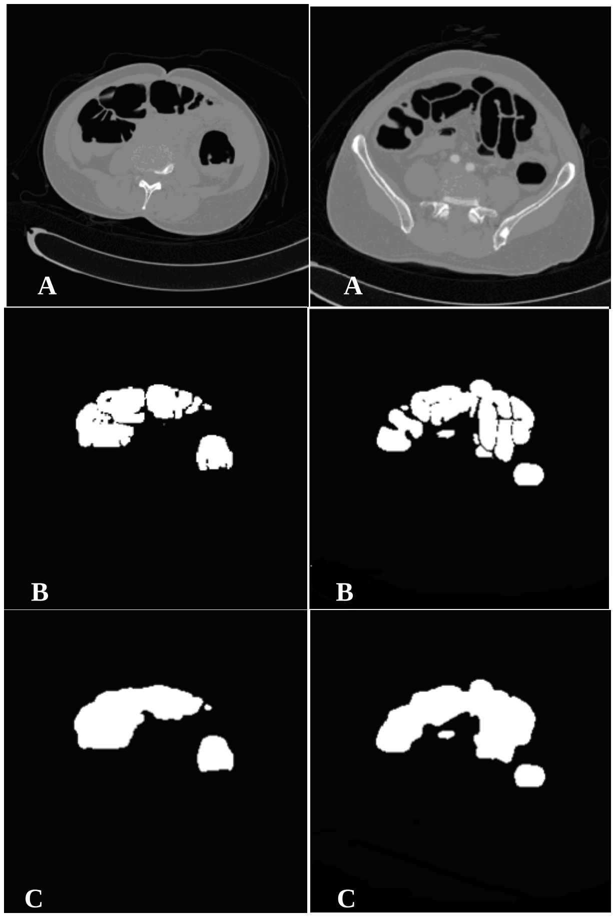

Figure 3. A- Original CT image.
B- Tresholding process output
C- CNN output

4. CONCLUSION

We have developed an automatic colon segmentation method for CT colonography using CNN. The technique is the combination of thresholding process and CNN. Density properties are utilized. Original CT images are passed through a threshold (-800HU) and then CNN is used to erase small objects and smooth sharp corners. Colon segmentation is considered in order to prevent time consumption while searching polyps in the colon region and reduce radiologists' interpretation time. It is shown that CNN approach is a powerful tool for colon segmentation and as an automatic detection algorithm decreases subjective errors. It is expected that the radiologists' diagnostic performance in the detection of the polyps will be increased with this method.

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