Application of the Neural Network for the Automatic Extraction and Measurement of the Peritoneum

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Abstract This paper proposed a method to extract and measure the peritoneum automatically. In this algorithm, firstly, the input image is normalized and the edge between the empty area and the monolayer of the flat cells are detected. Then, the peritoneum area is extracted by the using a three layer neural network. And then measurement of the peritoneum is performed. We tested this algorithm by using the real-world image. The experiment results show that this method is very efficient and effective.

Keywords: medical image processing, neural network, peritoneum extraction and measurement.

1. Introduction

There are plenty of literatures on medical image processing. These works can be further classified into many sub-fields such as brain image processing and analysis [1]-[5], eye fundus image analysis [6], heart motion detection [7], blood image analysis [8], bone image processing [9], and fingerprint and footprint recognition [10] [11], and so on. However, there is few for the peritoneum extraction and measurement. This paper focuses on this problem and discusses the automatic extraction and measurement of the peritoneum.

The people without any medical knowledge may ask the following questions. What is the peritoneum and what is its function? Why is it necessary to extract and measure it? First, let us answer the previous question. In 1730, James Douglas gave the first modern description of the peritoneum [12]. He observed that it was smooth and flat, and was lubricated by a fluid to preserve it from the inconvenience of continuous friction. As observed by Douglas, the main function of the peritoneum and other serous membranes is to reduce the friction between moving organs. As shown in Fig. 1, the peritoneal serous membrane consists of a monolayer of flat cells on a basement membrane, and a layer of connective tissue, of variable thickness and structure, containing cells, blood vessels, lymphatic vessels, and a nerve fiber immersed in a connective matrix. Fig. 2 shows a sample of parietal peritoneum under SEM (scanning electric microscopy). Normally, the peritoneum is very thin, 30 – 40 µm in the greater omentum and somewhat thicker in the diaphragm, parietal, and visceral peritonea.

Now, let us answer the second question. For example, if the urine of a person does not come for several days, he/she is seriously ill. To absorb his/her urine in his/her body, it is necessary to inject more sugar content into his/her body. However, too much sugar content will make the peritoneum getting thicker. According to the research of Topey et al, normally, the

Fig.1 Diagram of parietal peritoneum.

Fig.2 Parietal peritoneum(SEM, ×100).
thickness of the sub-mesothelial compact zone is 50 – 60 μm without CAPD (continuous ambulatory peritoneum dialysis). If he/she receives CAPD for more than 6 months, this value will become more than 1000 μm. Therefore, it is very important to monitor the

Fig. 3 Process from sampling to peritoneum measuring. change of the thickness of the peritoneum.

Fig. 3 shows the present process from taking peritoneum sample to measuring. It includes the following steps. (1) Take a mesothelial block right under the epidermis of the stomach, and cut it into slices, (2) Put each slice on a small piece of glass, dye it with chemicals, then put another piece of glass over it. Two pieces of glasses are stuck together to be fixed. In such way, the specimens are constructed. (3) Put each specimen under the electronic microscopy and take a photo of it. (4) Measure the thickness of the peritoneum by medical doctors. It is worth to notice that, when dyeing the slice of the sample at step 3, the monolayer of flat cells and the layer of connective tissue will become different color. This makes it possible for medical doctors to measure it by hand.

Fig.4 is an example photo of the peritoneum. To measure the thickness of the peritoneum by hand is very time-consuming and hard labor, and the precision of the measured result is low. Here, we propose to extract the peritoneum and measure it, automatically, that is, to extract the monolayer of fat cells and measure its thickness (width), as shown in Fig. 4. The proposed algorithm is as follows. First, the input image is normalized, and the area between the empty area (air) and the monolayer of flat cells is extracted. Then, a 3-layer neural network is employed to separate the empty area, monolayer of flat cells, the connective tissue, and others. And then, the monolayer of flat cells is detected and measured. The following gives the details of these processing.

2. Algorithm Description

2.1 Normalization

For the input full-color image \( F(i, j) \), it is normalized by

\[
G_k(i, j) = \frac{F(i, j)}{C_2 - C_1} \times 255
\]

where \( i \in \{0, ..., M-1\}, j \in \{0, ..., N-1\}, k \in \{R, G, B\}, C_2 = \max \{ F(i, j) \}, C_1 = \min \{ F(i, j) \} \), and \( M \) and \( N \) are the horizontal and vertical size of the input image, respectively.

2.2 Edge and its Regression Line Detection

When measuring the thickness of peritoneum by hand, to make the problem be easy, it is usually to leave an empty area (air) over the monolayer of the flat cells. Therefore, there exists a clear edge between the empty area and the monolayer of flat cell. This is also employed in our algorithm as given below.

The normalized input image \( G(i, j) \), is scanned vertically from top to bottom and from left to right. If the following requirement is satisfied, that is,

\[
\sum | G_k(i, j) - G_k(i, j+1) | > T_{\text{lim}}
\]

the pixel \( (i, j) \) is considered as an edge point, and is denoted by \( P(i_E, j_E) \). And the detected edge is expressed as \( S_E = \{ P(i_E, j_E) \}, i_E \in \{0, ..., M-1\} \). It is necessary to notice that the scanning for the \( i \)-th column will be interrupted and is shifted to \( (i+1)\)-th column when an edge point is detected. Therefore, there is only one edge point is detected for each column.

For the edge \( S_E \), its regression line of \( x \) on \( y \), as shown by the blue line in Fig. 4, can be obtained according to the coordinates of \( P(i_E, j_E) \in S_E \), and is given by

\[
L_{\text{ref}}: \quad y = \frac{s_{xy}}{s_{xx}} x + \left( -\frac{s_{xy}}{s_{xx}} \bar{x}_c + \bar{y}_c \right)
\]

where \( \bar{x}_c \) and \( \bar{y}_c \) are the average of and \( i_E \) and \( j_E \), respectively, \( s_{xx} \) is the variance of \( i_E \) and \( s_{xy} \) the covariance between \( i_E \) and \( j_E \), \( i_E = 0, 1, ..., M-1; j_E = 0, 1, ..., N-1 \).

This line will be used as the reference in measuring the thickness of peritoneum later. Here and after, it is called as reference line and denoted as \( L_{\text{ref}} \).

2.3 Extraction of Peritoneum Area

At present, after being dyed, the monolayer of flat
cell becomes blue, and the connective tissue red. Because there exist a little difference among the dyed slices, and also the lighting may change when taking photos from the electronic microscopy, the color of images may change a little. For example, the color of the monolayer of the flat cell may become blue, light blue, or dark blue. This can be also said to that of connective tissue. Therefore, it is difficult to separate them by thresholding. Here, we employed the neural network to do it as shown below.

The input image is fed to the input of the neural network. The neural network has three layers. The input layer has 42 neurons (8 neurons for average value of R, G, and B in $3 \times 3$ window, respectively, and 18 neurons for the average hue in the same widow), the hidden 42, and the output 3 (red, blue, white). The training is performed according to momentum BP algorithm [13]. The neural network outputs three images corresponding to red, blue, white, respectively.

The peritoneum area is extracted from the red output image by the following way. The reference line, $L_{ref}$, is shifted to the right by a step $\Delta x$. The shifted reference line is denoted as $L_{right}$. The number, $N_{right}$, of white pixels of the red output image lied on $L_{right}$ is counted, and the rate, $N_{right} / M$, is calculated. This processing is repeated until $N_{right} / M < T_{blue}$ is satisfied ($T_{blue}$ is a predetermined threshold value). When this repetition stops, the position of $L_{right}$ is considered as the bottom edge of the peritoneum area. In the similar way, the top edge of the peritoneum area can be also determined. The peritoneum area extracted from the input image in Fig. 4 is shown in Fig. 5, bounded by the top edge and bottom edge.

$$H_{avg} = \frac{1}{MK} \sum_{j=0}^{M-1} h_j$$
$$H_{min} = \frac{1}{K} \min \{ h_0, ..., h_{M-1} \}$$
$$H_{max} = \frac{1}{K} \max \{ h_0, ..., h_{M-1} \}$$
$$S = H_{avg} (M^2 + (M \cdot s_{xx})^2)^{1/2}$$

where $K$ is the manifaction of the electronic microscopy.

3 Experiment Results
All algorithms are implemented with MS Visual C++ on Windows 98. The values for $T_{blue}$, $T_{white}$, $\Delta x$ are set 150, 10%, and 5 dots, respectively. And $K$ is 4000. Fig. 6 shows five input images and the extracted peritoneum areas. We also tested the other images. The measured results are summarized in Table 1. All experiment results are satisfactory.

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<th>File Name</th>
<th>$H_{min}$</th>
<th>$H_{max}$</th>
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<th>$S$</th>
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2.4 Measurement of Peritoneum Area
The thickness $h_i$ ($i = 0, 1, ..., M-1$) is obtained by counting the number of the white pixels lied on the normal line from top edge to bottom edge, as shown in Fig. 5. Then, we can obtain the average thickness $H_{avg}$, the minimum thickness $H_{min}$, the maximum thickness $H_{max}$, and the area $S$ according to the following equations.

4. Conclusions and Future Works
This paper proposed a method to extract and measure the peritoneum automatically. We tested this algorithm by using the real-world images. The experiment results show that this method is very efficient and effective. The next step is to measure the volume of the peritoneum by using the multiple consecutive images. This is our future work.
Fig. 6. The row on the left gives 5 input images, the row in the middle shows the red output of the neural network, and the row on the right shows the extracted peritoneum areas, correspondingly.
Reference


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