ON OPTIMIZATION OF REGION GROWING PROCEDURE FOR COMPLEX CT IMAGES[1]

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Abstract. A method of automatic detection of human brain region in computed tomography (CT) images is described in this article. The main attention is paid to complex CT slices obtained in temporal or nasal level. Method is suitable for identification of region of interest (ROI) after surgery operations of brain as well. In cases mentioned above brain region may be fragmented; it can have contacts with other tissues with similar X-ray absorption properties; it may be not covered by bones as well. In such cases automatic brain region identification requires more sophisticated algorithms. The algorithm described below uses filtering and morphological approaches for identifying the biggest grey particles and particle growing technique for selection of correct areas. Experimental results were obtained that show the algorithm in the most cases completely removes tissues of skin, eyes and bones. The accuracy of brain identification was evaluated by comparison with areas defined by experts. The method was suggested to use as the first stage of image processing in automatic brain disease detection software.

Key words: computed tomography, region of interest, image filtering, region identification algorithms

1. General Information

CT images of human brain contain a variety of objects like skin, eyes, ears, nose, bones, gristles, etc. However a proper analysis of human brain diseases requires clear identification of brain ROI in CT images [1, 3]. Especially brain tissue identification is required in automatic methods when computer software is used for evaluation of brain diseases [7]. In such cases one of the starting steps of image processing is detection of brain areas. The identification of human brain is usually not the main problem of image processing and it is

considered as simple and fast processing stage. It is true in the most conventional brain images where brain is completely surrounded by bones or skin is relatively thin. However there are special cases of patients to whom surgery operations were performed. The other class of images is obtained when CT is taken in cheekbone, temporal or nasal level [5]. Then brain tissues may have contacts with skin and they may not be surrounded by head bones. These complex images require a deeper analysis and take more time for brain region detection. In this article a relatively simple algorithm is proposed which is consequently fast and suitable for complex and usual CT brain images as well.

2. Design of Processing Algorithm

There are four stages in algorithm for automatic definition of the ROI in CT images (Fig. 1). The first stage is preprocessing. The initial brain area selection is accomplished by removing extraneous objects that aren't part of human tissues. The second stage is filtering by low pass filter with the purpose of enhancement of the largest compact objects corresponding to gray level of brain.
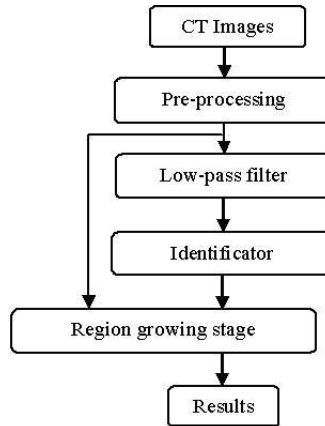

Figure 1. Flowchart of images processing algorithm.

The third stage of algorithm is identification of the objects in CT images. The special object separation is used which evaluates the quantity of objects of interest enclosed by head bones. The last stage is region growing. ROI is selected using contouring data of objects of interest and bone areas. In this stage the complex CT images with surgery holes in bone areas and with rather complicated images at the same time can be evaluated.

2.1. Image pre-processing

The purpose of pre-processing is removing of tomograph headrest artifacts from images [2]. This stage consists of two steps. During the first step the ROI is defined by selection of any grey point inside area of analysis. The second step is selection of area of analysis.
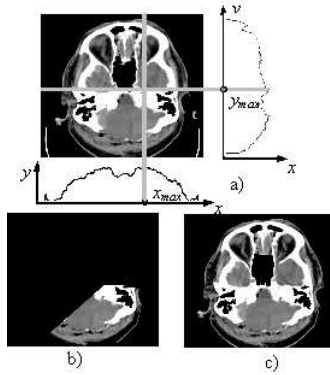
Figure 2. An example of region selection: a) selection of coordinates of brain area; b) after one step of region selection; c) after four steps of region selection.

A single point of brain area can be selected using two graphs (Fig. 2 a) that represent non-black pixel count in vertical and horizontal directions. The maximums in these graphs represent start coordinates $P(x_{max}, y_{max})$ of region of analysis. The second step is dedicated for brain area selection and for this purpose any morphological operation which can segregate a single object can be used. We used a simple pixels shifting algorithm. At first two identical sized image matrixes A and B were used. Suppose that in the matrix A the brain area is available. Then seed pixel $P(x_{max}, y_{max})$ of brain area was transferred to the B matrix. All process of transfer from matrix A to matrix B was realized by the following logical operations (2.1):

$$
\begin{aligned}
&\text{If} \quad A(x, y+1) > 0 \& B(x, y) > 0, \\
&\text{then } B(x, y+1) = A(x, y+1); \\
&\text{If} \quad A(x+1, y-1) > 0 \& B(x, y) > 0, \\
&\text{then } B(x+1, y-1) = A(x+1, y-1).
\end{aligned}
\tag{2.1}
$$

An example of intermediate results of pre-processing is shown in (Fig. 2 b). For complete selection of object in the matrix A it is enough to repeat such algorithm four times in the following directions: top - bottom, bottom - top, left - right, right - left, and in the result an object without headrest artifacts will be selected.

2.2. Image filtering

The main concept of using low pass filter is based on the idea that brain occupies the biggest part of grey tissues in CT images. The other CT objects like bones and tomograph headrest are assumed to be removed from image and the main problem is differentiation between brain, skin, and eyes tissues. If the brain area is continuous or divided into several relatively large and compact areas then low pass filter with narrow bandwidth should eliminate the rest of smaller objects. Visually the effect of low pass filtering may be understood as blurring of image. There are many methods of low pass filtering and blurring however they differ in speed of processing. We have used filtering in frequency domain [2, 6] which can be obtained by multiplying 2D image spectrum by low pass filter function and then retransforming spectrum back to time domain. The speed of this method is improved by using the fast Fourier transform and pruning of some spectral components. An ordinary filtering procedure is given in equation (2.2):

$$S(n,m) = \sum_{x=0}^{511}\sum_{y=0}^{511} s(x,y)e^{2\pi j(nx+my)/512};\tag{2.2}$$

$$S_\mathrm{B}(n,m) = S(n,m)\cdot F(n,m), \quad n,m=0,1,\ldots,511,$$

$$S_\mathrm{B}(x,y) = \frac{1}{512^2}\sum_{n=0}^{511}\sum_{m=0}^{511} S_\mathrm{B}(n,m)e^{2\pi(nx+my)/512},$$

where $S(n,m)$ is spectrum of image $s(x,y)$; $S_\mathrm{B}(n,m)$ is spectrum of blurred image $s_\mathrm{B}(x,y)$; $F(n,m)$ is function of low pass filter; variables x,y correspond to time domain pixel coordinates, variables n,m correspond to vertical and horizontal frequency respectively.

Low pass filter function may be selected in various ways. It was chosen rectangle function because it allows calculating only some needed spectrum components and eliminates the need of multiplication. This function is defined as (2.3):

$$F(n,m) = \begin{cases} 1, if(n\leq \mathrm{BW}; n\geq 511-\mathrm{BW};\\ m\leq \mathrm{BW};\ M\geq 511-\mathrm{BW};)\\ 0, otherwise.\end{cases}\tag{2.3}$$

In equation (2.3) abbreviation BW means low pass filter bandwidth. The recommended value of BW is in the range from 3 to 5 units.

Finally, after blurring procedure a detection of region may be performed. In the simplest way region can be obtained by using threshold function defined as (2.4):

$$s_\mathrm{B}(x,y) = \begin{cases} l1, & \text{if } s_\mathrm{B}(x,y)\geq \mathrm{TH};\\ 0, & \text{if } s_\mathrm{B}(x,y)\leq \mathrm{TH};\end{cases}\tag{2.4}$$

$$x=0,1,\ldots,511;\ y=0,1,\ldots,511.$$

where TH is a threshold value; the choice of TH depends on the characteristics of initial image before filtering.
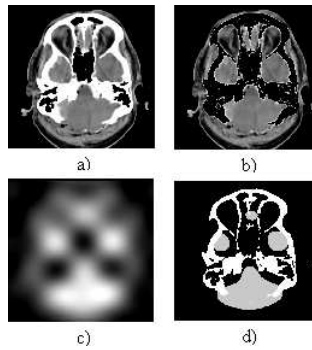
Figure 3. An example of image filtering: a) primary image; b) removed bones areas; c) filtered (blurred) image; d) image with approximated region of brain (lightened region).

The effect of described technique is depicted in (Fig. 3). As shown in the figure the first image was pre-processed by removal of white pixels. Then, filtering procedure causes image to become blurred.

Thereafter the threshold function (2.4) was applied. The detected regions are lightened in the lower right image. Starting from these approximate regions a further algorithm should be applied for accurate specification of contours of the brain regions.

2.3. Brain region identification

In this section an algorithm for objects identification with respect to bone areas that enclose the seed ROI is presented. This algorithm starts with image division into equal size squares (Fig. 4) with side length p and coordinates of center l, m. The straight lines that are drawn from centers of squares are used for identification.
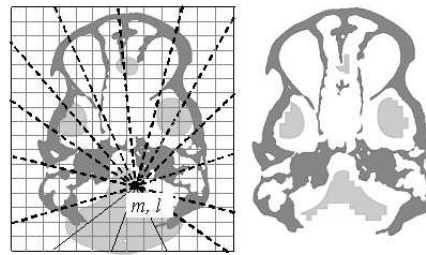
Figure 4. An example of brain region identification: a) line drawing example; b) result after levels of enclosing evaluation.

Let's denote as the straight line which is drawn in direction $\theta_k = 2\pi k/n$ $k = 0, 1, \ldots, n - 1$, here $2\pi/n$ is the step of lines, k running number of lines, n total number of lines for one square.

Some of straight lines can strike bones areas and when it occurs then state of line is changing. We introduce function $\varphi(L_{lmk})$ for evaluation of the state of each square as follows:

$$\varphi(L_{lmk}) = \begin{cases} 1, & \text{if line crosses the bone area,} \\ 0, & \text{otherwise.} \end{cases} \quad (2.5)$$

After implementation of (2.5) formula the separation is required. For this purpose we define parameter α_{lm} which shows how much each square are covered by bones areas. The α_{lm} in percents is calculated by formula (2.6):

$$\alpha_{lm} = \frac{\sum\limits_{k=1} n\varphi(L_{lmk})}{n} \cdot 100\%. \quad (2.6)$$

It is necessary to evaluate the level of enclosing by bone areas of each square after. For this purpose threshold γ is used to separate the set of squares in two parts. If $\alpha_{lm} > \gamma$ then we say that object is quite enough enclosed by bone areas, thus the square belongs to area of interest. In other cases grey level pixels of the square are removed. The same is done with all squares that cross any pixel of bone area.

2.4. Region growing
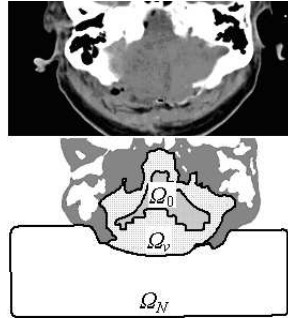
Figure 5. An example region growing and desired region selection.

Let we have an object Ω_0 enclosed by bones areas (Fig. 4). We used an region growing method similar to dilation algorithm [4] which creates an object Ω_n in each step n. The initial object Ω_0 is usually smaller than Ω_v desired (Fig.5). The problem is to choose the number ν which is optimal for some visual criterion. The region growing process leads to the following sequence of sets Ω: $\Omega_0 \subset \ldots \subset \Omega_{n-1} \subset \Omega_n \subset \Omega_{n+1} \subset \ldots$.

For determination of optimal value ν which is related to visual acceptability of the region of interest we used the following criterion:

$$\nu = \arg \max_{n} \frac{L_B(\Omega_n)}{L(\Omega_n)}. \tag{2.7}$$

Here $L_B(\Omega n)$ is the length of the growing region Ω_n contour part contacting to bone area and $L(\Omega_n)$ is the total length of this contour.

3. The Experimental Results

A lot of experiments showed that presented automatic four stages of algorithm can select brain area of CT images. It must be taken into account that developed algorithm is universal and able to work not only with complex images but with ordinary images too. The algorithm detects brain area using approximation which produces identification errors.
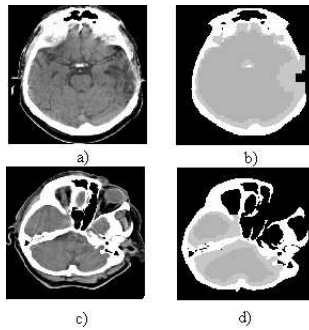

Figure 6. An example of automatic selection of region of interest.

First, the region selection precision depends on seed area shape (Fig. 6 b, d, dark grey area in the center of image) which derives after brain area identification (2.2). Second, dependences are from bones areas shape which is random for all images. As we can see on image example (Fig. 6 b) part of expanded region is overgrown outside of ROI and its part is inside. An evaluation of automatic brain detection was performed by estimating ratios of manually defined areas and automatically detected ROIs. 124 complex images were analyzed. In (Fig. 6 a, b) there is an example of brain area which is not completely surrounded by bones and there is an example of temporal CT slice with detected ROIs in (Fig. 6 c, d).

In (Fig.7) a histogram is shown of integral area error obtained by comparison between automatically and manually selected ROIs. The variable of horizontal axis is relative error which is divided into intervals of 10 %. On the vertical axis is percent of the images from total number 124.

As we can see the greatest part of analyzed images – about 75% – have relative area error less than 20%. The number of images with error more than
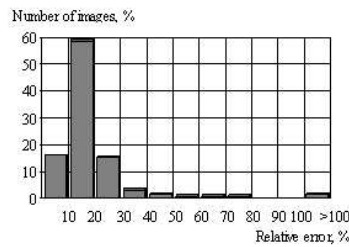
Figure 7. Error evaluation of automatic ROI selection, when $\gamma = 90$.

20% is rapidly decreasing. The area of ROIs was discovered wrong in three images (2,4%) only. There is a possibility to improve the results by developing new principles of optimal growing criteria ν.

4. Conlusions

1. Experimental investigation showed that comparative simple algorithm introduced for identification of regions of interest in the images of computer tomography works both in the case of conventional brain images and in the cases of complex images after surgery operations, and in the other special cases.
2. Comparison of the results of automatic analysis with the regions of interest estimated in the same images by experts pointed that in the 75% of images difference of areas assigned in automatic way and manually was less than 20%.

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