Brain segmentation tools under uncertain conditions for radiotherapy treatment planning

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Abstract

Objective: Radiotherapy Treatment Planning (RTP) is a procedure to plan the irradiation treatment which is usually simulated on a conventional simulator before applying it on the patient. The main goal is to deliver the adequate irradiation dose to a tumour without causing severe damage to surrounding normal and health tissues.

Material and methods: The major weaknesses of current RTP systems come from their rendering methods since most of them use surface rendering rather than volume rendering. All target objects and other critical organs are required to be modelled with interactive contouring slice by slice. The sizes of the segmentation objects are not accurate and some of small but critical organs sometimes may be neglected.

Results: Image segmentation is currently used into several medical imaging applications that involve diagnosis or treatment. Segmentation of volumes is an essential tool for the radiation therapy treatment of the cancer. One of the key organs that must be protected during the irradiation treatment is the brain. Nowadays, high resolution computed tomography (CT) data are required to perform accurate 3D treatment planning, and therefore there is the demand for quick but at the same time accurate segmentation tools. Inappropriate contours results have been performed for the cases where uncertain conditions are appeared (like position of the body in the table and metal material of the bed).

Conclusions: In this work we presented an algorithm that can be used for the accurate semi-automatic segmentation of the brain in three dimensions (3D) from CT images. Our method, which is currently in clinical use, is basically composed from an edge detection algorithm and statistical extreme values technique (outliers).

Introduction

A major field of application for volume visualization in medicine is the diagnostic radiology. One of the reasons is that radiologists are skilled in reading cross-sectional images. Another reason is that many diagnostic tasks such as tumour detection and classification can be done based on cross-sectional images [1-4]. Furthermore, 3D visualization of these objects from CT requires robust segmentation algorithms, which are not yet available. A number of different applications, like craniofacial surgery, neurosurgical planning and radiotherapy planning could be note the importance of different segmentation techniques [5-12].

Especially for the radiotherapy planning, the object is to focus on the radiation as closely as possible to the target volume, while avoiding side effects in healthy tissues. 3D visualization of target volume, organs at risk and simulated radiation dose allows an interactive optimization of treatment planning [13-15].

Many segmentation methods for 3D medical images are developed, which may be roughly divided into three classes: thresholding, edge- and region- based methods. Principally the brain region is embedded in the regions where the grey level values are different compared with the surrounding area and in the regions with similar grey level values [5,6,7,20]. For the first case due to the lower contrast than the surrounding bones can be easily detected using thresholding-based methods [3,4,9]. For the second case, unsatisfactory segmentation results were found for different data sets in cases where gaps and bridges were introduced. The basis of our approach is the edge detection algorithm, one of the most common methods used in image segmentation [21-22]. In our case the process must be initiated and therefore the user must give the starting point for the algorithm manually. The greatest benefit of this method is its algorithmic simplicity. Therefore, we have to introduce a measure to compare the accuracy of the segmentation results, which allow us to sample the segmented region using statistical methods based on the outlier theory. False alarms contours may be introduced like extreme values. The acceptance or rejection of these contour values could be introduced based on a specific confidence region values.

Material and methods

Brain segmentation in computed tomography is the delineation of neuroanatomical structures; outlines of brain structures can be drawn on images to indicate the extents of those structures. In general, is a very difficult and time-consuming process [17,18].

General segmentation of the human brain involves defining anatomical structures by primary borders, corresponding to grey or white matters or by secondary borders, which are knowledge-based anatomic sub-division within a grey or white matter. In this work an improved boundary tracking technique would be proposed for segmenting the organ [12,14,19,22]. There are two main cases: (i) the ordinal case where the brain grey pixels values are different of the table or the mask (in case of the radiotherapy) and (ii) the case where the

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head grey pixels values are similar with the other objects close to the
brain pixel values [8,16]. In the last case the results, for some slices, are
unsatisfactory giving false alarms segmentation results. To solve this
problem, an improved segmentation method is proposed based on the
outlier’s theory.

- For the simple case the only problem is when the algorithm extends
  the region of interest (Figure 1). In this situation a stopping criterion
  (red line) must be specified to control the segmentation process.
  Extending experiments suggests that a threshold of 5 cm², for
  the small area region until the spinal canal would be appropriate.
  After that measure the algorithm would be stopped. Similarly, the
  algorithm uses a constant threshold selection with levels 80 to 88
  Hounsfield values for the brain area justification.

- For the second case, where different objects closed to the brain
  bones have similar grey values, an improved segmentation method
  would be proposed based on the outlier theory.

  - The algorithmic steps for the procedure are:
    ✓ Calculate the periphery measure for all the contours.
    ✓ Find the maximum value of the periphery measure from all the
      slices.

    Calculate the new measure \( \text{dif}_i = \sqrt{\text{max}_{\text{periphery}} - \text{current}_{\text{periphery}}} \),
    where \( i \) is the contour number (Figure 2). The outliers that probably
    needed to be removed are presented into the graph.

    Calculate the average and the standard deviation of the measures \( \text{dif}_i \).

    Calculate the confidence intervals \( CI = \text{dif}_{\text{max}} - k \times \text{dif}_{\text{std}} \), where
    \( k \) is the acceptance rate. The choose of the \( k \) value is very important
    and many times difficult. It could be done by trial and error or by
    iteratively procedure, starting with a proposed value (for example 95%)
    and decreasing or increasing depending on the direction. In this work
    we use an iteratively approach; an approximate 49% of acceptance was
    found for this example (Figure 3).

    If a measure value is less than the CI value, \( \text{dif}_i < CI \), then this
    contour would be removed. Similar assumptions take place for the
    opposite direction.

    A linear interpolation takes place between the remained contours.

    A CT tomographic sequence of 8 bit grey scale images of a size 512
    × 512 in which change the shape, and the orientation of the objects
    was used. Figure 4 illustrates the 2D visual results from the false alarm
    segmentation method for different slices and figure 5 presents the

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Figure 4. False brain segmentations for different slices. From left to right: 34, 35, 36.

Figure 5. Improved brain segmentation results using the proposed method. From left to right: 34, 35, 36.
Figure 6. Visual results for 3D brain segmentation

Figure 7. Thresholding technique. Where \( C(i,j) \) contour value and \( T_{\text{table}} \) is the table value threshold

Figure 8. Intermediate slice interpolation.

Figure 9. Presentation of the linear point interpolation
A novel approach for the segmentation of the brain is introduced in this work. The current method combines an edge detection algorithm, outlier techniques and an interpolation methodology. Our solution is integrated into a virtual simulation system and has been clinically validated and from our trials it is proven that the brain can be segmented with high accuracy in real time. However, there is still room for improvements especially on the propagation of the detection path as well as on the automatic detection of the starting point in order to eliminate the user's manually intervention.

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