A KNOWLEDGE-GUIDED ALGORITHM FOR BRAIN LESION DETECTION

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1. Introduction

The delineation of brain tumor in CT or MRI sequences is important in many medical research environments and clinical applications. It is extremely useful in treatment planning and evaluation. Currently in many medical centers, 3-D tumor volumes are obtained by stacking the boundaries of tumors traced manually or semi-automatically on 2-D image slices. The human visual system is an ideal mechanism for quickly extracting a general description of an image. However, in the detailed analysis of subtle features, manual methods are not only tedious but also subjective, leading to substantial inter and intra-observer variability. Furthermore, it is difficult to obtain accurate evaluation of therapeutic efficacy based on manual delineation, since measurements of tumor volumes based on human observation are not reproducible.

This paper addresses the problem of the automatic detection of brain lesions in x-ray computed tomography (CT) imagery. Automatic detection of lesions is a non-trivial problem. Typically the boundaries of lesions in CT images are of single-pixel width, and the gradient at the lesion boundary varies considerably. As many studies show, these characteristics of lesions within CT images, in conjunction with the generally low signal-to-ratio of CT images, render simple boundary detection techniques ineffective.

We propose a knowledge-guided tumor detection algorithm. The algorithm applies multiscale morphological operations to CT images with the guidance of both anatomic and physical knowledge. The knowledge is used to select the initial slice within a CT image series, determine the apt size of morphological operators, link features extracted at different scales and eliminate irrelevant features. The algorithm is both data- and goal-driven. The experiments of the algorithm is described.

2. Multiscale Image Analysis using Morphological Operations

In the field of computer vision, multiscale analysis is an important technique for extracting interesting features from images. In low level vision processes, a smoothing process is often applied to images before the extraction of desired features. In general, we can get fine features from operators of small scales and coarse information from operators of large scales. In many applications, no single scale of smoothing is sufficient. The multiscale analysis technique can be used not only to eliminate fine-scale noise but also to separate events of different scales arising from distinct physical processes.

In this paper, we apply multiscale morphological operations to brain tumor image analysis. The mathematical morphology approach is powerful in studying many vision problems [LuH92]. In general, morphological opening and closing can be viewed as smoothing operations. An opening filter can remove objects with size smaller than the structure element, break narrow parts of a region into subregions and smooth the rough edges of object contours, therefore the regions extracted from a filtered image may not be identical to the corresponding regions in the original image. A closing operator with a disk structuring element smoothes object contours, fuses narrow breaks and long thin areas of a region and fills in small holes and gaps on the object contour. Morphological filtering of an image by an opening or closing operation corresponds to the ideal bandpass filters of conventional linear filtering. If we consider the size of B r as the scale parameter, as r changes from 1 to infinity, the filtered images and r form a scale space.

The morphological operations can be extended from binary into gray-scale images by introducing the concept of umbra. The umbra is the volume below the gray level surface. In gray scale images, dilation is accomplished by taking the maximum of a set of sums, and erosion is accomplished by taking the minimum of a set of sums. Hence gray scale dilation and erosion have the same complexity as convolution. However, instead of doing the summation as in convolution, minimum or maximum is performed. The set is defined by the structure element used in the dilation or erosion.

In gray scale images, the desired features can occur at any gray levels. Indeed, we cannot differentiate foreground from background pixels without the knowledge about the desired features. Based on the definition of opening and closing operations in gray level images, an opening operation can mean 'closing' to some regions and 'opening' to others. Hence the decision on applying opening or closing is dependent on the gray scale distribution model formed by its neighboring regions. In CT images, the desired features can occur at any gray levels. Based on our study, we discover that brain lesions have the following characteristics:

1. brain lesions can occur in different shape and size,
2. the brightness of the lesion varies depending on individual,
3. the boundaries are often fuzzy and sometimes do not form closed curves,
4. the brightness and the texture within the region of lesion are often inconsistent, and
5. brain lesion can have the same or opposite contrast as the surrounding anatomy.

Our study on the behavior of brain tumor in morphological scale space showed[LuH92] that behavior of brain tumor can be described by selecting proper multiscale morphological operations and scale parameters. If the brain tumor is lighter than its surrounding area, a sequence of opening operations can be applied to the gray image to extract the tumor boundaries, otherwise a sequence of closing operations can be used. In the multiscale opening-and-closing filtered images, the bright areas do not change monotonically with the parameter r., and they are not sensitive to small holes and cavities. The dark areas increase more rapidly than the opening filtered images. As the scale parameter increases, small dark regions are merged with neighboring regions instead of being eliminated as those in the opening filtered images. In general, the regions in the opening-and-closing filtered images have smoother boundaries than the filtered images by opening or closing alone and can also be used to extract lighter regions.

Based on the above study, we have constructed the following algorithm for detecting brain tumors.

3. Detecting Brain Tumors Guided by Knowledge

Our algorithm is both data- and goal-driven. The following knowledge sources are used to guide various computational steps in the algorithm:

- Normal brain anatomy. For example, lateral ventricles, straight sinus, and falx cerebri in CT images, and third and fourth ventricle in MR images. These objects are relatively easy features to be identified and extracted from the images and therefore they can be used as landmarks to guide the processes in our algorithm.

- Physical knowledge. It includes scanning angle with respect to the orbitomeatal plane, initial scanning location and the thickness of the image slices. In particular, MR imaging is multiparametric and the signal contrast depends on proton density, T1 and T2 relaxation times, and blood flow. This type of knowledge can be used to predict the occurrence and location of the anatomic landmarks and to hypothesize the locations of tumors.

• Physicians' knowledge. We use physician's knowledge about brain image characteristics to locate brain tumors and deal with difficult cases in which the tumor boundaries are either not discernible or ambiguous.

• Knowledge about object behavior under multiscale segmentation operators. Object can behave differently under different 3-D segmentation operators and at different scales [LuJ92]. For any selected 3-D segmentation operator, the behavior of objects in the scale space will be an important knowledge source for the reasoning processes in the system.

The algorithm consists of the following major computational steps:

(1) Selecting an initial slice of CT images. The initial slice is selected based on the scanning parameters and the estimation of the appearance of the tumor in the scanning direction. Ideally the initial slice should contain strong features of brain tumor.

(2) Selecting an appropriate sequence of operators. *a priori* knowledge of intensity contrast of the brain lesion is used to select either opening or closing operations. If a region of interest is lighter than the surrounding regions, a sequence of opening operations is applied to the gray scale image, otherwise a sequence of closing operations.

(3) Object segmentation. The object segmentation is performed based on the histograms of the filtered images at different scales. As the scale of opening or closing operator increases, the histograms of the filtered images provide better information to separate objects occurring at different gray levels. A clustering algorithm is developed to separate objects with different gray level distributions. The program operates on histograms across multiple scales. It groups the gray scales based on their histogram values and their distance to the next immediate gray scale that has non-zero histogram value. The stable group of clusters obtained from the histogram of the filtered image at the minimum scale is used to extract objects. Each cluster corresponds to one class of objects which have the gray levels within the cluster. The stability of clusters is measure upon the consistency of clusters across several different scales. Thus, objects are separated based on their gray level distributions in the image.

(4) Identifying the features of interest. We can uniquely identify the desired features such as tumor based on knowledge such as geometric shape and possible location.

(5) Update reference area. The reference area is a subimage of a slice that must contain the feature of interest. In the initial slice, the reference area is the entire image. Once we have detected the feature of interest in one slice, we can compute an area within which the feature extends to the two immediate neighboring slices of images in the sequence. The histogram should always be computed from the reference area and the reference area should be updated at every slice.

4. Experimental Results

Figure 1 (a) shows a subimage of a CT image which contains a brain lesion with a necrosis area. Figure 1 (b) shows the histogram of the image. The histogram has one mode and two heaps. The two heaps represent the brain lesion and the lateral ventricles. Let's assume the desired features are the lateral ventricles and the brain lesion. Apparently there are no clear clusters to represent the two heaps. Figure 1. (c) and (d) show the histograms of the filtered image by morphological opening with structure elements of disks of radius 2 and 3. It is obvious the histograms in (c) and (d) provides more information in separating the two heaps. Our clustering program found a stable group of three meaningful clusters from the histogram of the filtered image by disk of radius 2. The group contains three clusters, 165 to 187, and 188 to 208, and 209 to 225. The segmented objects are shown in (e), (f) and (g). The tumor and the lateral ventricles can be easily identified from (e) and (g) respectively provided we have geometric knowledge about the desired features.

5. References

[LuH92] Yi Lu and Laurel Harmon, "Multiscale Analysis of Brain Tumors in CT Imagery," *21st Applied Imagery Pattern Recognition Workshop, SPIE,* Oct. 14-16, 1992.

[LuJ92] Yi Lu and Ramesh Jain, "Reasoning about Edges in Scale Space," *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Vol. 14, no. 4, April, 1992, PP. 450-468

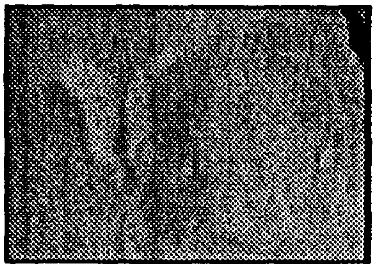

Figure 1. (a) Input image.

Figure 1 (b) Histogram of the image in (a)

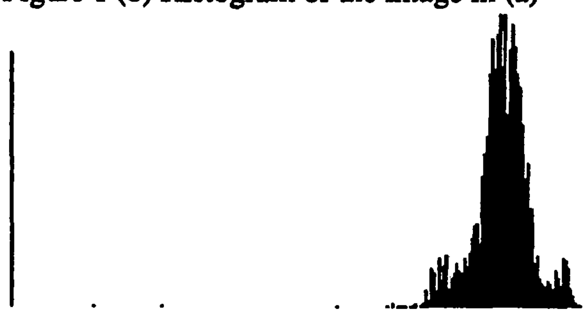

Figure 1. (c) Histogram of the image filtered by an opening operation with a disk of size 2.

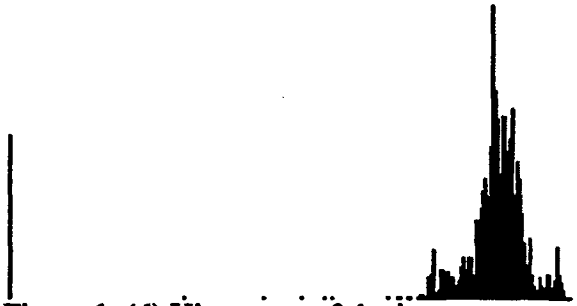

Figure 1. (d) Histogram of the image filtered by an opening operation with a disk of size 3.

Figure 1. (e) Objects have gray levels between 165 and 187.

Figure 1. (f) Objects have gray levels between 188 and 208.

Figure 1. (g) Objects have gray levels between 209 and 225.