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ENCHANCEMENT OF IMAGE SEGMENTATION METHODOLOGY IN MEDICAL IMAGE PROCESSING

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Abstract:

Brain tumor segmentation in magnetic resonance imaging (MRI) is considered a complex procedure due to the variability of tumor shape and the complexity of localization, tumor size and texture. Manual tumor segmentation is a tedious task, prone to human error. Therefore, this study proposes an automated method that can identify tumor slices and tumor segments across all image slices in volumetric MRI brain scans. First, a set of algorithms in the preprocessing stage are used to clean and normalize thedata collected for brain tumor segmentation MRI.

Keywords: MRI, Image segmentation, Edge segmentation, Region segmentation.

Introduction:

Medical imaging is an important contouring step when planning radiotherapy. Computed tomography (CT) and magnetic resonance imaging (MR) are the most widely used diagnostic x-ray techniques. Medical images.Segmentation ofmedical images, identifying organ or lesion pixels from background medical images such as CT or MRI images, is one of the most challenging tasks in medicalimage analysis including providing provides important information about the shape and volume of theseorgans. Earlier systems were built on top of traditional methods such as edge detection filters and mathematical methods. Designing and extracting these features has always been a development concern.The promising capabilities of deep learning methods have made it a prime choice for image segmentation, and especially medical image segmentation. Especially in the last few years, deep learning-based image segmentation has received a lot of attention and highlights the need for a holistic review. To the best of our knowledge, no comprehensive evaluation has been performed specifically of medical image segmentation using deep learning techniques. There are several recent investigative articles on medical image segmentation, such as and have looked at different types of medicalimage analysis, but with little emphasis on the technical aspects of image segmentation. medical.

Literature review:

Li et al. (2004) introduced an interactive segmentation vehicle based on a graph reduction technique very similar to that of Boykov and Jolly (2001a). It has two main steps. The first stage is the object marking phase, where strict constraints are defined so that regions are defined as either permanentin the background or permanent in the foreground. They use histogram cuts with segmentation technique which greatly increases the segmentation speed and can quickly provide segmentation results to the user. The second step is a boundary editing step where the individual vertices of the segment can be moved around until the user is satisfied.

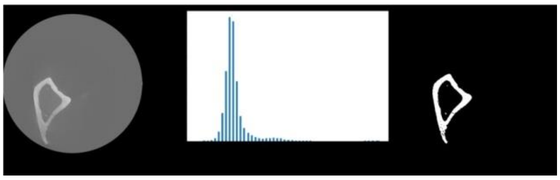
Blake et al. (2004) describe an image segmentation method that works without any user input. Most image segmentation techniques use user-defined parameters. to get an algorithm to learn the parameters from the image data and then perform segmentation based on those parameters. They use a database of images with correctly segmented results to test their approach.

Rother et al. (2004) presents an innovative way to segment an image into foreground andbackground areas. The segmented image is represented by a histogram constructed in such a way that minimal cost reduction on the histogram results in better image segmentation. Image pixels are represented by nodes on the histogram. The weights of the edges of the graph are then determined by a cost/energy function. This cost function will depend on both boundary and area pixel attributes.

Image segmentation based methods for Threshold Resonance Imaging

Threshold method is one of the most popular techniques for image segmentation. Threshold technique works with pixel intensities and histogram analysis. This method uses a specific value as the threshold value (T) to convert the gray scale image into a binary image. There are two different methods for creating thresholds as global and local methods. The global method uses T as the threshold for the entire image, then each pixel below the T value becomes the background (black) and each pixel above the T value becomes the foreground (white). The corresponding histogram and MRI images and global threshold segmentation images establishing an accurate threshold value can be difficult due to similar intensities and pixel values in different regions.

Figure 3 Method Between Global, (A) Input Mri Image, (B) Histogram Between 70170 Range, (C) Output Image Threshold



General Image

The edges of the edge-based segmentation are the boundary of the an object in an image, so bytaking the edge of each object we can divide the objects in the image by their edges. Edge segmentation uses gradients (originated) to find the edges of the image. First,theimage is smoothed using a Gaussian filter to reduce noise. Second, the intensity and direction of the edge are determined by performing a 2D spatial transformation of the smoothed image using the Sobel operator. The third stage is zero-maximum removal, which scans the image deeply to remove any unwanted pixels that may not be part of the edges. each pixel is tested as a local maxima in its neighborhood in the direction of the gradient. Region-based segmentation The region-based segmentation approach uses pixel continuity and is based on the concept of homogeneity. These algorithms look for similarities between adjacent pixels by grouping pixels withsimilar characteristics such as intensity, texture, color, and pixel shape into unique regions. There are two methods of area a. developing regions and mergers and splits. Region development is considered the simplest technique and it starts with a few starting points,grouped into n different sets and selected basedon characteristics and regions ofinterest. With seeds,regions will grow by connecting adjacent pixels based on their characteristics. Areas are selected to be as uniform as possible. the criterion is the pixel intensity threshold value, knowledge of the histogram can be used to determine the optimal threshold value for the breakpoint.

Regional segmentation of the brain image

Regional segmentation of the brain image. Three different stages of planting from left to right, seed selection, connection of seeding points with neighbouring areas of the same character and completion stage. In general, region-based segmentation performs better than edge-based segmentation in noisy images.

Methodology

Typical noise in an MRI image appears as a small random change in intensity within an individual pixel group or a subgroup. These differences can be large enough to lead to false segmentation. Intensity Normalization The pixel intensity values of each MRI slice were normalized to the same intensity range to achieve dynamic range consistency. Then histogram normalization was applied to stretch and alter the original histogram of the image and cover all gray levels of the image. higher contrast than the original image because histogram normalization improved the contrast of the image and provided a wider range of intensity transitions. This approach demonstrated better classification of pathological tissues Background Segmentation Previous knowledge has shown that background intensity values of MRI brain slices are often close to zero to allow background segmentation. The ability to remove and exclude the background of region.

The human brain is divided into two hemispheres with an approximately bilateral symmetry around the MSP. The two hemispheres are separated by the longitudinal fissure, which represents a membrane between the left and right hemisphere.

Brain Tumors Location Identification

Many tumor-segmentation methods are not fully automated. These approaches require user involvement in selecting a seed point. Usually, the MRI slices of a patient are interpreted visually in MRI brain images and expand the high-contrast regions in a nonlinear manner. This action would increase theintensity difference between the brain tumor and the original image.

Image Segmentation Algorithm:Input: MRI Image

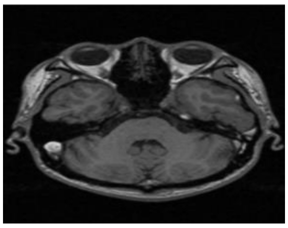
Process:

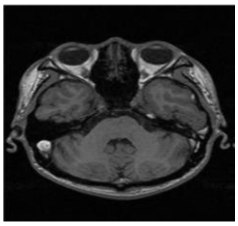
Intensity Normalization; Background Segmentation; BrainTumorsLocation Identification;

End Process;

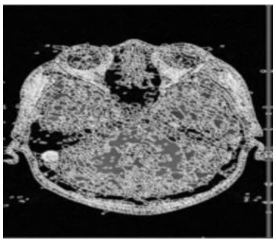
Output: Segmented Brain Tumor Image;

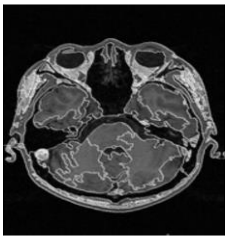
Results and Discussions:



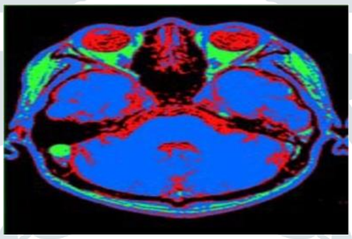


Orginal MRI Image **Intensity Normalization**





Partition image **Tumor identification**



Final segmentation

For each MRI image, optimum performance was achieved by the 92% accuracy for correctly classifying the collected dataset by cross validation. The assessment of predictors depends on both F- statistic value and p-value because a p-value less than 0.001 is insufficient for a predictor. Instead, the predictor must also hold a high F-statistic value. The high F-statistic value indicates that the classes significantly separated from one another.

Conclusion:

Imaging with MRI imaging is subjective and highly dependent on the expertise of the clinician. This method reduces the clinician's evaluation time from 3–5 hours to5,10 minutes without significantly reducing diagnostic accuracy. Indeed, the proposed method can recognize and segment MRI brain abnormalities (tumors) on T2w, T1w, T1cw and FLAIR images. The segmentation technique reduces manual input, operates quickly, and exhibits high accuracy compared to manual segmentation, and it is effective in brain tumor segmentation because it considers not only the local characteristics of the tumor, such as gradients, but also based on global characteristics. , such as intensity, edge length, and region length. Although the accuracy achieved is high compared to other segmentation techniques, for brain tumor segmentation. Such slow speed is attributed to processing a large number of MRI slices of 512_512 pixel resolution with a high number of repetitions used to achieve the required accuracy.

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