CT IMAGE LABELING USING SIMULATED ANNEALING ALGORITHM

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ABSTRACT

Segmentation of computed tomography (CT) head images is required by many image analysis procedures for quantitative measurements of human spontaneous intracerebral brain hemorrhage (ICH). In this work we describe a stochastic method for segmentation of CT head images based on simulated annealing (SA). In the proposed method, the segmentation problem is defined as the pixel labeling problem with labels for this particular application set to: background, skull and ICH, and brain tissue. The proposed method is based on the Maximum A-Posteriori (MAP) estimation of the unknown pixel labels. A Markov random field (MRF) model has been used for the posterior distribution. The MAP estimation of the segmented image has been determined using the simulated annealing algorithm. Experimental results have demonstrated good results and proved the usability of the method.

1 INTRODUCTION

An important step in medical image analysis techniques is segmentation. Segmentation of computed tomography (CT) head images is important for quantitative analysis of human spontaneous intracerebral brain hemorrhage (ICH) [10, 3]. An accurate segmentation of ICH is required for image-based measurement of the ICH volume. The most difficult step in image-based measurement systems is often the segmentation of the region of interest. After the region is determined it is easy to compute the desired measurement value, e.g. the volume. There has been and currently is a lot of research aimed at segmentation of medical images. A number of different techniques have been applied to the problem of CT head image segmentation including clustering algorithms [2, 13, 12], neural networks [4, 15, 1], morphological methods [14, 16], and knowledge-based methods [11]. An overview of stochastic image analysis methods can be found in [6]). In this work we describe a stochastic method for segmentation of CT head images based on simulated annealing (SA). The paper is organized as follows. A definition of the pixel labeling problem is presented in Section 2. An overview of SA algorithm for image segmentation is given in Section 3. Results and discussion are provided in Section 4 . Finally, a conclusion is given in Section 5.

2 PIXEL LABELING PROBLEM

The segmentation process can be viewed as a pixel labeling problem. The process of segmenting individual pixels is therefore viewed as the process of assigning labels to individual pixels.

In general, the labeling problem consists of accurately labeling objects from a given object set with labels from a predefined set of labels. In image analysis, the objects are image regions which may consist of a single pixel or a number of pixels constituting an image region. In pixel labeling, a set of objects is a set of image pixels.

The pixel labeling problem is formulated as follows. A label set is defined as $L = \{l_1, l_2 \ldots, l_G\}$, where G is the number of labels. The label set represents the pattern classes in the image. The object set is defined as $P = \{p_1, p_2, \ldots, p_M\}$, where M is the number of objects. It can be observed that the possible number of objects/labels combinations is M^G. The labeling problem is constrained by a number of rules describing the possible labeling of neighboring objects and/or possible labels for certain objects.

A number of algorithms have been applied to the labeling problem including backtracking tree search [8], knowledge-based approaches [11, 5], neural network-based approaches [9], and simulated annealing [7].

In this work a simulated annealing algorithm described in [6] is used for segmentation of CT head images.

3 SIMULATED ANNEALING SEGMENTATION ALGORITHM

The segmentation algorithm tries to estimate the true pixel labeling denoted by $\mathbf{x}=\{x_1, x_2, \ldots, x_M\}$. The image given for segmentation can be viewed as a realization of the random field. Let the random field be denoted as $\mathbf{Y}= \{Y_1, Y_2 \ldots, Y_M\}$, where Y_t is the feature vector associated with the t-th pixel. A certain amount of information for the labeling process can be extracted from the neighborhood of each pixel. The pixel neighborhood influence is described using a Markov Random Field (MRF) model of the statistical dependence among the neighboring pixels. Given a set of observed feature vectors (our image), **Y**=**y**, and the contextual information as an MRF, P(**X**=**x**), the problem lies in finding the 'optimal' estimate of the true labeling **x**. The MAP (Maximum A-Posteriori) method estimates $\hat{\mathbf{x}}$ that maximizes the posterior probability of **X**=$\hat{\mathbf{x}}$, given **Y**=**y**.

$$P(\mathbf{X}=\mathbf{x}|\mathbf{Y}=\mathbf{y}) = \frac{P(\mathbf{Y}=\mathbf{y}|\mathbf{X}=\mathbf{x})P(\mathbf{X}=\mathbf{x})}{P(\mathbf{Y}=\mathbf{y})}$$

Such a problem of finding an 'optimal' pixel labeling, defined above, is highly complicated. In order to find a MAP estimate we have to minimize a complicated function with the number of variables equal to the number of pixels in the image. *Simulated annealing* is a method of function optimization capable of finding the global extreme avoiding the entrapment of the algorithm in the local extreme. SA makes no assumptions about the smoothness of functions to be optimized, but the process of optimization is computationally demanding. In this paper we describe the application of SA algorithm to the problem of segmenting CT images. The algorithm itself has been altered in a way to become more faster, but still keep the good performance when applied to a problem at hand. The algorithm is as follows:

1. Choose an initial temperature T.
2. Initialize $\hat{\mathbf{x}}$ by choosing x_t as the color $\hat{x}_t$ that maximizes $P(Y_t = y_t|X_t = x_t)$ for each pixel t.
3. Perturb x into z by randomly choosing site t and setting its label to a random value in the interval {0, 1, ..., G-1}.Let

   $$\Delta = U(\hat{X}_t = \hat{x}_t|Y_t = y_t) - U(\hat{X}_t = z|Y_t = y_t)$$

   If $\Delta > 0$ then replace $\hat{X}_t$ by z else replace $\hat{X}_t$ by z with probability $e^{\Delta/T}$.
4. Repeat step (3) N_{iter} times.
5. Replace T by $f(T)$ where f is the monotonically decreasing function.
6. Repeat steps (3)-(5) until frozen.

In the above algorithm, $P(.|.)$ is a conditional probability density function of the gray levels in the image for a specified label. The probability density function is approximated with a Gaussian function of the form

$$P(.|.) = e^{-\frac{(y_t-\mu_l)^2}{2\pi\sigma_l}}$$

where variance and mean values are extracted from the image histogram as described below. G is the number of labels in the image, and $U(.|.)$ is the energy function that defines the energy of a single pixel. This is what makes the difference between the original and the proposed version of the algorithm. In the original algorithm $U(.|.)$ is the energy of an entire image. The energy U consists of two parts, the first part describes how well the pixel's label fits its gray value, and the second part describes how compatible the pixel is with its neighborhood in terms of its label. The first part can simply be calculated using the expression $1 - P(.|.)$, where $P(.|.)$ is the probability density function. The neighborhood influence is calculated by checking the 4-neighborhood (up, down, left, right), to see weather the pixel's label matches with the surroundings. If not, the energy U is increased by k-times a constant factor, k being the number of pixels in the neighborhood which do not match the viewed pixel label. The choice of a cooling function f, the initial temperature T, and the number of iterations is done experimentally. The temperature must be lowered slowly to prevent entrapment of the algorithm in the local minima. There is a number of ways to lower the temperature. A good choice is:

$$T_{k+1} = \frac{ln(1+k)}{ln(2+k}T_k$$

, where T_k is the kth execution of the outer loop of the algorithm. In this work the following function is used:

$$f(T) = \alpha \cdot T$$

The distribution of gray values in the image is assumed to be normal. Image regions of different brightness correspond to different modes in the histogram. Mean values μ_l and variance values σ_l for histogram modes corresponding to different image regions can be determined manually or automatically extracted from the image histogram.

The automatic procedure for histogram mean and variance values is as follows.

1. Smooth the histogram by convolving it with a Gaussian function. By doing this the histogram becomes smooth allowing us to easily extract peaks and determine means μ_l for all image regions corresponding to the histogram modes.
2. Calculate cross-correlation factor between histogram at site μ_l and a Gaussian function with increasing variance. By assigning the variance that produces the largest cross-correlation factor we determine variance σ_l for histogram means.

4 RESULTS AND DISCUSSION

The conducted experiments included segmentation of CT images of resolution of 512x512. The number of labels used in the experiment was equal to three. The labels correspond to the following image regions: brain, skull and ICH, and background. The choice of a cooling function in the SA was a linear function with a constant factor of 0.975. Initial temperature was set to 50 and number of iterations to one quarter of the total number of pixels in the image. The proposed algorithm is implemented in C language on a SUN Ultra 1 workstation.

The experimental results for two examples are shown in Figure 1. It can be observed that the algorithm accurately segmented different regions of interest. However, an additional step of higher level reasoning is required to correctly classify letters on the background as not belonging to skull region, and to distinguish skull and ICH regions.

The performance of the SA algorithm considering the quality of segmentation is satisfactory but this is shadowed by the lack of speed. Although some changes are introduced to the algorithm to boost its speed, there is still room for improvement. The execution time for segmentation of a 512x512 CT image is 10-12 minutes.

5 CONCLUSION

The SA method proposed in this work has shown good results when applied to the problem of segmentation of CT images. However, the method has shown to be computationally complex opening room for improvements of the algorithm.

The future work will include further optimization of the algorithm to improve the execution speed, as well as adding another higher-level region labeling to distinguish various regions in the image.

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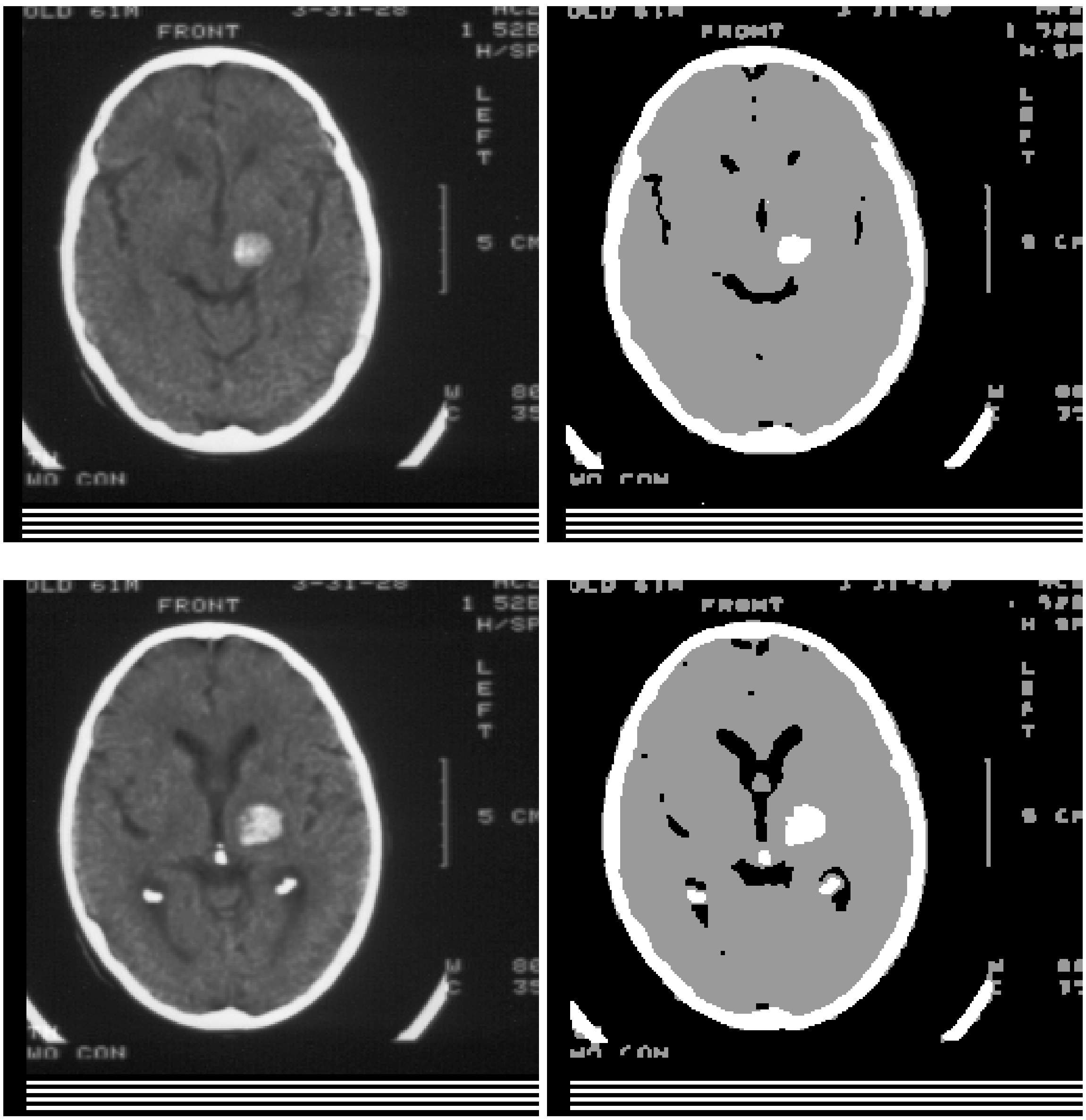

Figure 1: Two examples of original and segmented images.