Multiresolution CT Head Image Analysis using Simulated Annealing

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Abstract

Segmentation of computed tomography (CT) head images is an important step in quantitative analysis of human spontaneous intracerebral brain hemorrhage (ICH). A new multiresolution probabilistic approach for segmentation of CT head images containing ICH region is presented in this work. In the proposed method, the segmentation problem is viewed as a pixel labeling problem. In this particular application the labels are: background, skull, brain tissue, and ICH. The proposed method is based on the Maximum A-Posteriori (MAP) estimation of the unknown pixel labels (i.e. the segmented image). 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 (SA) algorithm. The multiresolution approach has been applied in order to speed up the SA algorithm. Experimental results have demonstrated good results and proved the usability of the method.

Keywords: image segmentation**,** simulated annealing, multiresolution, computed tomography

1. Introduction

One of the most important steps in procedures for medical image analysis is segmentation. In particular, segmentation of computed tomography (CT) head images is an important step in quantitative analysis of human spontaneous intracerebral brain hemorrhage (ICH). An accurate segmentation of ICH is required for image-based measurement of the ICH volume. In general, the most difficult step in image-based measurement systems is segmentation of the region of interest. Once the region is determined it is easy to compute the desired measurement value, e.g. the volume.

A number of techniques have been applied to the problem of CT head image segmentation including clustering algorithms (Bezdek 1993, Loncaric 1996, Loncaric 1996/2), neural networks (Chiou 1995, Ozkan 1993, Amartur 1992), morphological methods (Loncaric 1995, Thomas 1991), and knowledge-based methods (Li 1993). An overview of stochastic image analysis methods can be found in (Dubes 1989).

In this work we describe a multiresolution stochastic method for segmentation of CT head images based on simulated annealing (SA). The paper is organized as follows. An overview of SA algorithm for image segmentation is given in Section 2. A description of the proposed multiresolution segmentation method is given in Section 3. Results and discussion are provided in Section 4. Finally, a conclusion is given in Section 5.

2. Simulated annealing algorithm for image segmentation

In this approach, the image segmentation problem is viewed as the pixel labeling problem. To define the pixel labeling problem, consider a set of objects (image pixels) and a set of object labels (pixel labels) $L=\{l_1,l_2, ...,l_G\}$ (Dubes, 1989). In image segmentation, the labels denote the pattern classes in the image. The pixel labeling problem consists in estimating the true pixel labeling $x=\{x_1, x_2, ..., x_M\}$. The stochastic formulation of the problem is as follows. The image is viewed as a random field, i.e. as a two-dimensional sequence of random variables. The realization of the random field is our image to be segmented, and is denoted $Y=\{Y_1, Y_2, ..., Y_M\}$, where Y_t is the feature vector associated with the *t*-th pixel. Information about neighborhood influence (context) enters the labeling problem through a Markov Random Field (MRF) statistical dependence among the neighboring pixels. Given se observed feature vectors, $Y=y$, and the contextual information as an MRF, $P(X=x)$, the pixel labeling problem is to find the 'optimal' estimate of the true labeling *x*. The Maximum A-Posteriori (MAP) method estimates $\underline{x}$ by maximizing the posterior probability of $X=\underline{x}$,

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

given $Y=y$. In order to find a MAP estimate we have to minimize a complicated function of *M* variables, where *M* is number of pixels in the image.

Simulated annealing is a method of function optimization that tries to avoid the pitfalls present in other methods for optimizing functions of many variables. There are no assumptions about the smoothness of functions to be optimized, but the process of optimization is computationally demanding The SA algorithm is as follows (Dubes, 1989):

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

   $$\Delta = U(\underline{z}|y) - U(\underline{x}|y)$$

   If $\Delta>0$ then replace $\underline{x}_t$ by $\underline{z}$ else replace $\underline{x}$ by $\underline{z}$ with probability $e^{\Delta/T}$.
4. Repeat (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

$$P(Y = y \mid X = x) = e^{\frac{-(y_t - a_t)^2}{}}$$

G is the number of labels in the image, and $U(.|.)$ is the energy function that defines the energy of a single pixel. 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 gray value. The first part can simply be calculated using the expression $1\text{-}P(.|.)$, 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, and in this work we have used:

$$f(T) = \alpha \cdot T, \quad \alpha \in \langle 0,1 \rangle$$

3. Multiresolution segmentation using SA

The problem in the practical realization of the SA algorithm is that even for a moderately sized image, e.g. *256 x 256* the number of variables (i.e. pixels to be labeled) in the optimization space is *65,536*. This number is even larger in case of higher resolution images. This is the reason for the large computational complexity of the algorithm leading to a long execution times. To overcome this difficulty and speed up the algorithm we have developed a multiresolution image analysis approach. The general idea is to reduce the number of variables to be optimized and thus reduce the computational burden. The proposed multiresolution SA algorithm is as follows:

1. Let S be the original image at resolution NxN
2. Let $\{S_0, S_1, \ldots, S_{k-1}\}$ be the multiresolution pyramid of k levels, where S_0=S, obtained by binary subsampling the original image S.
3. Perform the SA segmentation on the image of the lowest resolution S_{k-1}.
4. **for** z=k-2, …, 0 **do** {multiresolution pyramid levels}
5. Obtain temporary image T by interpolating image S_{z-1} by a factor of 2.
6. Clear list L
7. **for** each pixel in T
8. Let $p(l)$ be an array of probabilities, $p(l)=P(Y_t=y_t|X_t=l), l=0, \ldots, G-1$
9. **if** p(pixel's label currently in T) is not equal to max $p(l)$
10. **then** add four pixels, obtained by expansion of pixel at lower resolution to list L. The four pixels in question are those expanded from the lower resolution and created from the same pixel as the one being checked
11. **endfor**
12. Perform SA segmentation of the image S_z using T as initial image and only test pixels from the list L.
13. **endfor**

In step 5 we conduct interpolation of the lower resolution image by pixel replication

Each pixel at the lower resolution is expanded to four pixels at the higher resolution which are labeled with the same label as in the previous level. Expansion is done by placing the pixel's label at site (x,y) to pixels, of the higher resolution image, at sites (2x,2y), (2x+1,2y), (2x,2y+1) and (2x+1,2y+1). In step 6 we clear the list L. This list contains a number of pixel sites in the form (x,y). These are sites that need to be checked in the next iteration of the SA algorithm, and the only pixels we work with during the segmentation. Labels placed in step 5 do not necessarily represent the best labeling, so it is necessary to perform a check of the each newly assigned label. The check is based on how the pixel's gray level fits the probability density function, of the gray levels, of the three types of regions present in the image (Steps 7-10). If the label inherited from the previous level is not the best, the entire cluster of four pixels is placed on the list for reassessment. The entire cluster is placed on the list so that the pixel's neighborhood is also reassessed. Each checked pixel is given its optimal label based on its gray level.
The segmented image and a list of pixels for reassessment created in this way is given in the step 12 to the SA algorithm.

4. Results and Discussion

The conducted experiments included CT images of resolution of 512x512. The multiresolution algorithm used four multiresolution levels starting at resolution 64x64 to 512x512. The choice of 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 M (the total number of pixels at current resolution).

The SA algorithm is relatively fast at the lowest resolution. At higher resolution, only a small portion of pixels is reassessed. The final effect of all this is that we get the same quality of segmentation but up to five times faster. The typical execution times are 11 minutes for the conventional SA algorithm, and about 3 minutes for multiresolution SA algorithm.

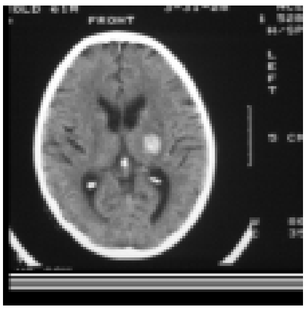

Figure 2Original image

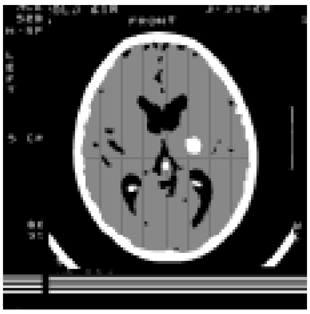

Figure 1 Segmented image

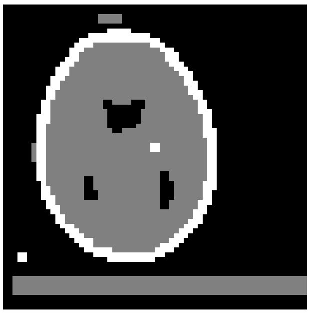

Figure 3 Segmented image at 64x64

Figure 4 Segmented image at 128x128

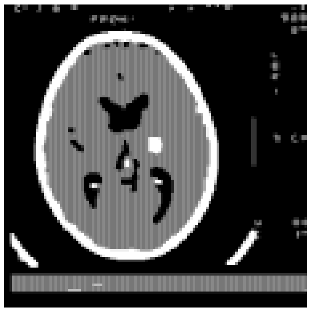

Figure 5 Segmented image at 256x256

5. Conclusion

The multiresolution SA method proposed in this work has shown good results when applied to the problem of segmentation of CT images. The method has shown to be computationally efficient compared to the conventional SA algorithm implementation.

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