CT IMAGE LABELING USING HOPFIELD NEURAL NETWORK

Domagoj Kovacevic and Sven Loncaric

Department of Electronic Systems and Information Processing
Faculty of Electrical Engineering and Computing
University of Zagreb, Croatia
E-mail: dkovacev@zesoi.fer.hr, sven@zesoi.fer.hr
Tel: +385-1-612-9891, Fax: +385-1-612-9652

ABSTRACT

In this work, a method for the computed tomography (CT) image labeling is presented. CT images used in this work are obtained from patients having the spontaneous intra cerebral hemorrhage (ICH). The images are segmented into three tissue classes (skull, brain, and ICH) and the background. The method consists of two steps. In the the first step, the image is divided into a number of regions using the K-means clustering algorithm. Regions used are dark, medium dark and bright region. In the second step, the regions are labeled using the modified Hopfield neural network.

The stable state of the network represents possible solution to the labeling problem. Simulated annealing is used as algorithm for network simulation.

1. INTRODUCTION

The problem of image region labeling is important step in processing of CT images. In a typical image analysis procedure the the image is first segmented into regions. In the following step it is necessary to determine the tissue type corresponding to each region. This can be done in several ways. There is a number of classical labeling algorithms that can be used for finding the solution of the labeling problems such as backtracking tree search algorithm [1]. Another possible approach is the use of expert systems which model human knowledge about the given problem [2]. This approach is convenient for easier representation of the knowledge that is otherwise difficult to represent using classical image processing algorithms. Neural networks have also been used for image labeling problems [3].

In this work the labeling problem is formulated as an energy minimization problem. The Hopfield neural network is used to minimize the energy function. The energy is a function of topological information extracted from the image and of the features of the image regions.

2. METHOD

The segmentation procedure consist of two steps. First, the image is divided into regions by clustering of pixel values into three clusters (dark, medium and bright) using the K-means clustering algorithm. The regions obtained by clustering are described by the cluster membership, size, brightness and by the list of regions to which they are adjacent.

The results of the image clustering is used as an input to the second stage of the procedure, where the regions are labeled with the tissue class labels (background, brain, skull, and ICH). The labeling is performed using the Hopfield neural network. The region labeling problem can be formally described in the following way [3]. Let $X = \{r_1, r_2, \ldots, r_R\}$ be a set of R regions and let $Y = \{l_1, l_2, \ldots, l_L\}$ be a set of L labels. The problem of assigning the correct label to each of the regions is referred to as the region labeling problem. The approach used in this work is to solve the labeling problem by minimization of an energy function. The energy function is formulated to have minimal value when all the necessary constraints are satisfied. The energy function is minimized using the Hopfield neural network. The Hopfield network with two-dimensional topology, consisting of R rows and L columns of neurons, is used in this work. Each row corresponds to one region and each column corresponds to one label. The label l_j is assigned to the region r_i if the activation of the j-th neuron in the i-th row is the highest among all neurons in that row, after the network has converged to a solution.

For a typical image the biggest dark region is background, the biggest medium bright region is brain and the biggest bright region is skull. For this reason the activations of the neurons that represent these regions are such that, for example, neuron representing membership of the biggest dark region to the background region is fixed to one and neurons representing mem-

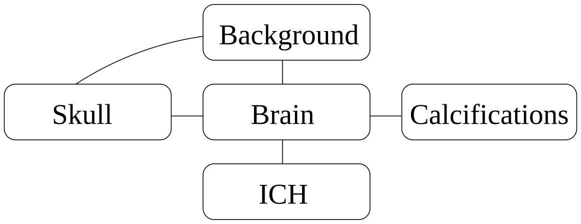

Figure 1: Possible neighborhood relations between tissue classes.

bership of that region to other tissue classes are fixed to zero. For that region activations are as follows:

$$V_{Ij} = \begin{cases} 1.0 & \text{if } l_j = \text{background} \\ 0.0 & \text{otherwise} \end{cases} \tag{1}$$

r_I is the biggest dark region and $V_Ij, j = 1, \ldots 4$ is the activation of neuron in I th row and j th column.

For other neurons activation functions are chosen in such a way to satisfy constraints imposed on the CT image. This constraints are formulated as energy terms which are then minimized by the network. The constraints and the associated energy terms are as follows:

1. *Single label constraint*: This constraint ensures that each region has only one label. The corresponding energy term is:

$$E_1 = -\frac{1}{2}\sum_i^R \sum_j^L S_{ij}^2 + \sum_i^R \sum_j^L \sum_{k \neq j}^L S_{ij} S_{ik} \tag{2}$$

   where S_{ij} stands for activation of the neuron in the i-th row and the j-th column. The first term maximizes the network activation while the second term introduces inhibitory connections between elements of the same row to ensure activation of a single neuron in that row.

2. *Label adjacency constraint*: In a typical CT image, only certain regions are allowed to be adjacent to each other. For example, it is not allowed for a region labeled as the skull to be a neighbor to a region labeled as the ICH. The allowed neighborhood relations are shown in Figure 1.

   Let $\mathbf{A}$ be a $R \times R$ matrix with elements a_{ij} equal to one if the region i is adjacent to the region j and zero otherwise. In addition, let $\mathbf{B}$ be a $L \times L$ matrix with elements b_{ij} equal to one if a region with label i cannot be adjacent to a region with label j and zero otherwise. Then the second constraint can be formulated as the energy term in the form:

$$E_2 = \sum_i^R \sum_k^R \sum_j^L \sum_l^L a_{ik} b_{jl} S_{ij} S_{kl} \tag{3}$$

3. *Region size constraint*: Regions belonging to class l are expected to have the area D_l. Note that this constraint is not an obligatory one. It just says that a region is more likely to be labeled as the class l, if its area is closest to the expected area of the regions labeled as l. The energy term is as follows:

$$E_3 = \sum_i^R \sum_j^L e^{-|(\ln(H_i/D_j))|} S_{ij}^2 \tag{4}$$

   where H_i is the size of i-th region and D_j is the expected size of the region belonging to class j. The expected sizes of the classes relatively to the image size for the background, brain, skull, and hemorrhage, are $0.5, 0.35, 0.1$, and 0.05, respectively.

4. *Region brightness constraint*: Regions belonging to class l are expected have brightness F_l. This constraint like the preceding one is not of an obligatory form. The associated energy term is:

$$E_4 = \sum_i^R \sum_j^L e^{-\frac{1}{M}|G_i - F_j|} S_{ij}^2 \tag{5}$$

   where M is the maximum brightness in the CT image.

The expected brightnesses of the classes on the scale $0-255$ for the background, brain, skull, and hemorrhage, are $18, 210, 100$, and 195, respectively.

The total energy is defined as the weighted sum of the energy terms defined above as follows:

$$E = c_1 E_1 + c_2 E_2 + c_3 E_3 + c_4 E_4 \tag{6}$$

Where c_i are the Lagrange multipliers used to impose significance on the energy terms. The required Hopfield network weights are derived from the expression for the total energy.

The mean field theory implementation of the Hopfield network has been used in this work [4]. According to the mean field theory the expected value V_{ij} of the neuron activation S_{ij} is given by:

$$V_{ij} = \frac{1}{2}(1 + \tanh(-\frac{1}{2T}\frac{\partial E}{\partial V_{ij}})) \tag{7}$$

where T is the parameter called temperature. As temperature approaches zero the activation function tanh

For a given CT image define the network topology, the energy function, and the temperature T^0.
Initialize neuron activations to random values between 0.2 and 0.5
repeat
  Update the output of each neuron asynchronously using its activation function.
  Decrease temperature using the expression $T^{k+1} = 0.99 * T^k$
until $\sum_i^R \sum_j^L \mid V_{ij}^{k+1} - V_{ij}^k \mid < 10^{-3} LR$

Figure 2: The algorithm for updating Hopfield network.

approaches the sigmoid function. The update procedure is as follows. The network is initialized to a random state with small values for all V_{ij} at high temperature to avoid converging to a local energy minimum. The activation function of neurons describing the biggest dark, medium dark, and bright region is set to constant as described in Equation 1 and for the others neurons in the net activation function is set according to Equation 7. The energy term from Equation 7 is obtained by substituting V_{ij} for S_{ij} in Equation 6.

The temperature is decreased at each iteration until the stable state is achieved. The algorithm for network simulation is based on the algorithm proposed in [5] and is shown in Figure 2: This method significantly outperforms standard Hopfield method which is in fact a special case of this method with temperature set to zero.

Another approach we tried was to use a stochastic network. In stochastic networks neuron activations are binary and the value of activation S_{ij} is 1 with probability V_{ij} and 0 with probability of $1 - V_{ij}$. Although it is possible to obtain similar results with this method as with the continuous one in this case results depend on starting conditions.

3. RESULTS AND DISCUSSION

The results of the proposed method are shown in Figure 3. The image size is 256×256 pixels gray-scale $0 - 255$. The clustered image has ten regions. The corresponding Hopfield network has forty neurons and some 300 weights.

Results of labeling with the proposed algorithm are shown in Figure 3 right. All regions are labeled correctly. The algorithm has good numerical stability since results do not depend on initial activations of the neurons. Method is though, very sensitive to values of multipliers in Equation 6. Best simulation results were obtained with following values: $c_1 = 1.0$, $c_2 = 0.1$, $c_3 = 0.1$, and $c_4 = 0.2$. Activations of neurons for ICH region, energy of network averaged over all neurons, and temperature as parameters of iteration number are shown in Figure 4. It can be seen from the figure that all neurons have similar activations until temperature drops to the critical temperature. At this point one neuron "wins" and suppresses activations of other neurons due the constraint described in the Equation 2. After this point energy of the network decreases significantly and the network settles into the stable state. Algorithms are implemented in C language and Khoros environment on a Sun Ultra 1 workstation.

4. CONCLUSION

In this work a method for labeling regions of the CT image is presented. The method is based on the modified Hopfield neural network with energy function formulated to describe the region labeling problem. The proposed method has shown good experimental results when applied to the problem of CT brain image labeling.

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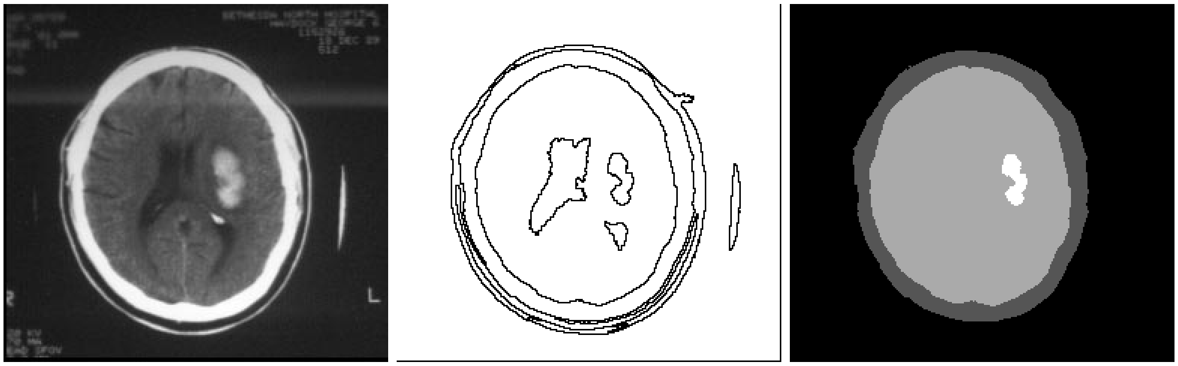

Figure 3: Original CT image (left), image regions obtained by clustering its histogram into three clusters (middle), and image labeled with the Hopfield neural network (right).

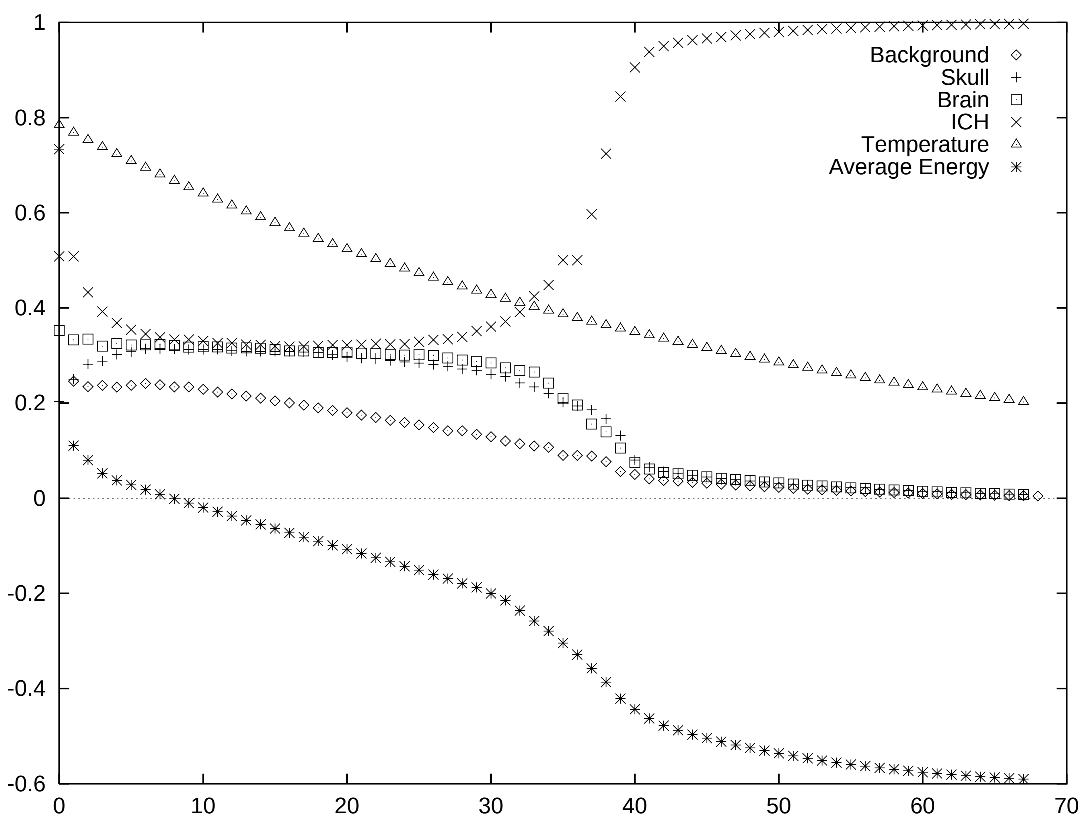

Figure 4: Neuron activations for region labeled by the network as ICH, average network energy and temperature as functions of iteration number.