

A Novel approach for Image Segmentation using SOM

¹P. Valarmathi, ²M. Aruna

^{1,2}Dept. of CSE, M.A.M College of Engineering, India

Abstract

This paper proposes a novel approach to extract image features like contour extraction and edge detection for image segmentation with self organizing properties for a network of adaptive elements. Segmentation is a collection of methods allowing to interpret parts of the image as objects. The object is everything what is of interest in the image and the rest of the image is background. Through experiments, the proposed approach will be intensively evaluated by applying a large number of segmentation tests to medical images.

Keywords

Image Segmentation, SOM

I. Introduction

Image segmentation refers to the process of partitioning a digital image into multiple regions (sets of pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image. Some of the practical applications of image segmentation are [3]:

1. Medical Imaging
 - Locate tumors and other pathologies
 - Measure tissue volumes
 - Computer-guided surgery
 - Diagnosis
 - Treatment planning
 - Study of anatomical structure
2. Locate objects in satellite images (roads, forests, etc.)
3. Face recognition
4. Automatic traffic controlling systems

The segmentation of an image can be carried out by different techniques that are based mostly on the discontinuity and similarity of the grey levels of an image. Gonzalez and Woods[1] propose several edge detection and segmentation techniques and Felzenswalb and Huttenlocher[2] propose yet different methods.

This paper proposes a novel approach to extract image features like contour extraction and edge detection for image segmentation with self organizing properties for a network of adaptive elements. Through experiments, the proposed approach will be intensively evaluated by applying a large number of segmentation tests to medical images.

Complete segmentation divides an image into non-overlapping regions that match to the real world objects. Complete segmentation divides an image R into the finite number S of regions R_1, \dots, R_S

$$R = \bigcup_{i=1}^S R_i, R_i \cap R_j = \emptyset, i \neq j$$

Partial segmentation is possible to find only parts with semantic meaning in the image (e.g., regions, collection of edges) which

will lead to interpretation in later analysis.

The SOM [4] belongs to vector quantization algorithms. Basically the SOM transforms high dimensional input data into a lower dimensional display, which is normally two-dimensional. The elements of the display are called as map units or cells. Each cell contains a reference vector (also codebook vector), which usually has same dimension as the image patterns. Optimization of the SOM is based on the quantization error in the reference vector space. The pseudo-code for the batch SOM is (Kohonen, 2001):

Initialize reference vectors m_i

Repeat until converged

For each neuron i collect a list (S_i) of input vectors x whose nearest reference vector belongs to neuron i .

Update each m_i using S_i .

End

Batch algorithm is better than the sequential algorithm because batch algorithm does not suffer from convergence problems. When dataset is redundant and large sequential algorithm can be used. Due to fast computation batch algorithm is preferred than sequential one.

Parameters that must be defined before the analysis are:

- Topology of the SOM map. Popular alternatives are sheet, cylindrical and toroid topology.
- Distance measure for computing the difference between data and reference vectors.
- Number of vector.
- Initialization of reference vectors. Initialization can be done in arbitrary many ways.
- Learning algorithm.
- Neighborhood function and corresponding dynamical parameters.

The neighborhood function plays central role in the SOM algorithm regardless of the type of the learning algorithm. Three frequently used neighborhood functions are presented in the fig [6].



Fig. 1:

Elements of the data that are close to each other and comprehend a disjunctive subset are said to belong to the same cluster. As a result of the SOM algorithm, n -dimensional data are presented in two-dimensional display. If the network is a two-dimensional array, the network itself generally limits the neighbourhood[5]. The definition of the neighbourhood presents two different cases, one if the network of nodes accepts that the neighbourhood is limited by the edges of the network itself, and

the other in case that the neighbourhood is not limited by the edges of the network.

II. Implementation

Kohonen's self-organizing maps are a type of neural network used to classify inputs of consistent but arbitrary dimension [7]. The most popular unsupervised training algorithm, it does not require a 'teacher' to direct the outputs. It does require training on a set of data.

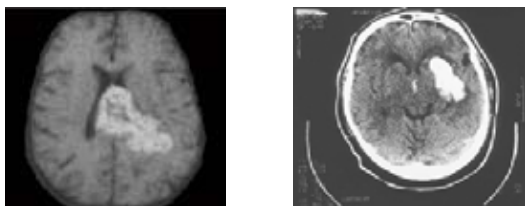
1. Allocate an $m \times n$ array
2. For each node in your array, allocate an N element array with initial values randomly distributed between 0 and 1. N is the number of dimensions of your input. These are your initial weights.
3. For each training input vector:
 - Select the node with the closest matching weights. Simple Euclidean distance is effective: $\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 \dots}$
 - Update the weights on this node
 - Update the weights on this node's neighbors

The only complication is the definition of updates and neighbors. I used three parameters: a decaying learning rate, a decaying radius and the distance from the best matching node. The decay is controlled such that at the final iteration, inputs have no further influence on themselves or their neighbors. The resulting equation for a node's update is: $w[i] = w[i] - \text{learning Decay} * \text{influence} * (w[i] - \text{input Weight})$.

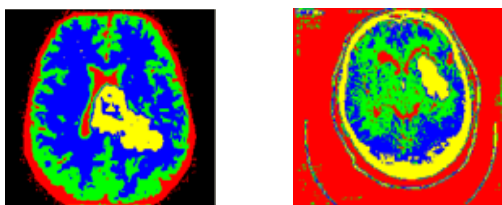
III. Results

Algorithm is implemented with different images as input signals. Fig. 2 and 3 shows the result of brain tumor after many iterations. For images that have not been previously segmented through grey levels, a grid network is preferred over a linear or annular network.

Input Images



After mapping



Segmented Images



Fig. 2:

Fig. 3:

IV. Conclusion

MR image segmentation is an important but inherently difficult problem in medical image processing. In general, it can not be solved using straightforward, conventional image processing techniques. Due to the characteristics of MR images, development of automated algorithms is challenging. There is a significant inter-patient variation of signal intensities for one same tissue type because of partial volume effect, inherent noise and wide range of imaging parameters, which affect the tissue intensities.

In this paper, we present Batch algorithm on self-organizing feature map. The proposed algorithm includes extra spatial information about a pixel region by using unsupervised training algorithm. It verifies that the neighboring pixels should have similar segmentation assignment unless they are on the boundary of two distinct regions. The simulation results demonstrate that the proposed algorithm works well. The further work is to compare the method with other existing approaches.

References

- [1] Gonzalez RC, Woods RE, "Digital Image Processing", Addison Wesley.
- [2] Felzenszwalb PF, Huttenlocher DP. "Image Segmentation using local variation".
- [3] Kohonen T. "Self Organization, Associative Memory", Springer-Verlag.
- [4] Kohonen T. "Self Organizing Maps: Optimization and Approaches", ICANN.
- [5] Constantino carlos, Reyes-Aldasoro, "Image Segmentation with Kohonen Neural Network SOM".
- [6] S. HAUTANIEMI ET AL. "Analysis and Visualization of Gene Expression Microarray Data in Human Cancer Using Self-Organizing Maps".
- [7] Yan Li, Zheru Chi, "MR Brain Image Segmentation Based on Self-Organizing Map Network".