Application of An Adaptive Self Organizing Feature Map to X-Ray Image Segmentation

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ABSTRACT

In this paper, a neural network based approach using a self-organizing feature map is proposed for the segmentation of X ray images. A number of algorithms based on such approaches as histogram analysis, region growing, edge detection and pixel classification have been proposed for segmentation of general images. However, few approaches have been applied to X ray image segmentation because of blur of the X ray image and vagueness of its edge, which are inherent properties of X ray images. To this end, we develop a new model based on the neural network to detect objects in a given X ray image. The new model utilizes Mumford-Shah functional incorporating with a modified adaptive SOFM. Although Mumford-Shah model is an active contour model not based on the gradient of the image for finding edges in image, it has some limitation to accurately represent object images. To avoid this criticism, we utilize an adaptive self organizing feature map developed earlier by the authors.[1] It's learning rule is derived from Mumford-Shah energy function and the boundary of blurred and vague X ray image. The evolution of the neural network is shown to well segment and represent. To demonstrate the performance of the proposed method, segmentation of an industrial part is solved and the experimental results are discussed in detail.

Keywords: X ray image, image segmentation, adaptive self-organizing feature map, Mumford-Shah model, active contour.

1. INTRODUCTION

In image processing, segmentation is one of the most important steps leading to the analysis of processed image data. Its main goal is to divide an image into two or several parts that have a strong correlation with objects or areas of the background. A number of algorithms based on such approaches as histogram analysis, region growing, edge detection and pixel classification have been proposed for segmentation of images. Segmentation methods can be divided into three groups according to the dominant features they employ[2]. First is the global knowledge based method – generally, the histogram of image features are used for global knowledge. Edge-based segmentation is the second one and region-based segmentation is the third. Edge-based segmentations rely on the edges found in an image by edge detecting operators. These edges denote the mark image locations of image discontinuities in gray level. But the image resulting from edge detection cannot be used as a segmentation result directly. Supplementary processing steps must follow to combine edges into chains that correspond better with borders of objects. Region growing techniques work well in noisy images where borders are extremely difficult to detect. Homogeneity is an important property for regions and is used as the main segmentation criterion in region growing. Active contour model integrates both edge detecting technique and region growing technique. So, the active contour model has the advantages of both methods. The use of energy – minimizing curves, known as active contour or snake to extract features of interest in images has been introduced by Kass, et al [3]. For instance, starting with a curve around the object to be estimated, the curve moves toward its interior normal and has to stop on the boundary of the object. In active contour model, the performance of segmentation depends on the ability to detect the edge of given image. Generally an edge-detector has been used to stop the evolution of curve representing the boundary of the desired object.

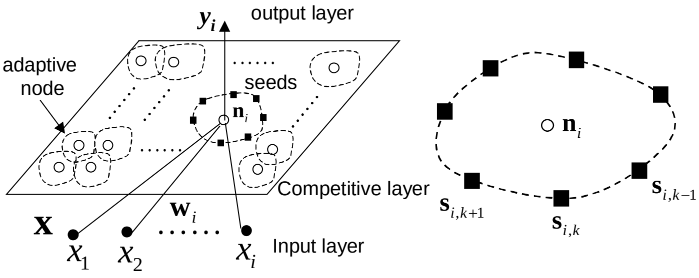
In the case of the X ray image, segmentation or detecting the edge is however considered to be rather difficult because of blur of the X ray image and vagueness of its edge, which are inherent properties of the X ray images. To overcome these properties, a number of images are generally needed for image processing to obtain the image information such as area of cross section or edges of the interested target objects. In tomography and laminography, blur and vagueness can be reduced through an iterative refinement procedure. But it requires long acquisition time to acquire a required number of images and also needs high cost.

To avoid such criticism, we propose a new segmentation algorithm for X ray image. The algorithm modifies the Mummford – Shah model [4] by the neural network, adaptive self organizing feature map. The model proposed by Mumford and Shah can detect the objects whose boundaries are not necessarily defined by gradient. [5]

The model, however, has the disadvantage that it can not well segment such objects having complex shapes since the model utilizes a contour globally acting over the whole object to be segmented. This scheme eventually enhances the description of the contour thereby improving the segmentation performance. In contrast to this, ASOFM (adaptive self organizing feature map) incorporated with the model employs as many desired number of contours to operate on the local region of the object. In other word, the proposed new model can detect edge and represent the boundary of segmented image with a set of smaller active contours by neural network parameters such as weights of nodes and positions of seeds. This active scheme combined with ASOFM is applied to several practical images such as industrial parts. The results show that in spite of low image quality, it can clearly segmented the objects from background.

2. ADAPTIVE SELF ORGANIZING FEATURE MAP FOR IMAGE SEGMENTATION

Figure 1 (a) shows the structure of the proposed adaptive SOFM (ASOFM). The basic structure of ASOFM is similar to Kohonen except that the nodes of Kohonen network are replaced by adaptive nodes. Each node has a limited number of seeds around its periphery to represent the geometric information near the node while the nodes of Kohonen do not have any geometric information. The learning rule consists of two stages: The first is leaning of nodes and the second is leaning of their seeds. The learning of nodes is executed in the whole input space and seeds are updated in local area around the nodes. When an input enters the neural network, the nodes of ASOFM are updated according to Kohonen learning rule in input space. After the Kohonen nodes are trained, a set of seeds for each node are assigned to represent a neighborhood geometry around each node as shown in Figure 1 (b). The $\mathbf{n}_i$ denotes the i th node and the $\mathbf{s}_{i,k}$ indicates the k th assigned seed of i th node. The updating rule of seeds is a competitive learning rule and is similar to Kohonen learning rule.[6] The details of learning process will be discussed in following sections.



(a) The Structure of ASOFM (b) The seeds of a node

Figure 1. Structure of an adaptive SOFM (ASOFM)

3. IMAGE SEGMENTATION USING ASOFM

3.1. The Procedure of Image Segmentation

The nodes of ASOFM represent the whole area of image and the seeds represent the local image information around each node. When the input image data enter the neural network (stage 1), we calculate the average intensity of the image. In general, the background has higher intensity than the objects, and thus, we can roughly estimate the background and object. After obtaining the average intensity, the initial nodes of ASOFM are assigned randomly in the region whose intensity is less than the average value and updated by Kohonen learning rule (stages 2,3). After leaning of all nodes, the seeds of each node are assigned. The seeds are initialized by a small circle with finite seeds (stage 4). Then, we calculate the average intensity value of regions, segmented by the contours. Based on these average intensity values, the learning of seeds and their Kohonen nodes are carried out, whose learning rule will be discussed in the next section (stage 5,6). After leaning of the seeds and nodes, the whole segmented image is obtained by merging the locally learned area by each adaptive node (stage 7). Until no noticeable changes in the segmented image are observed, learning process is repeated (stage 8). This procedure is illustrated in Figure 2.

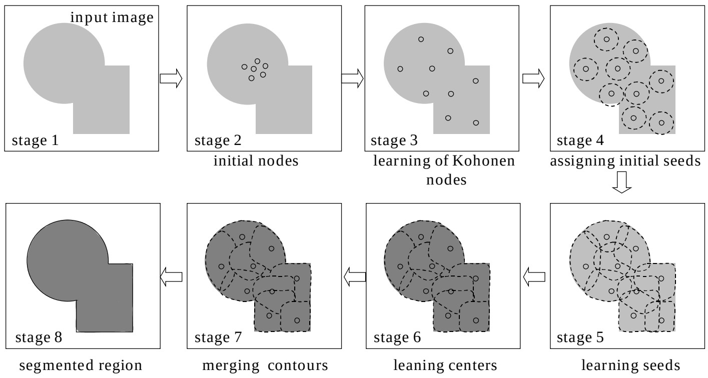


Figure 2. The procedure of learning neural network

3.2 Learning rule of ASOFM based on Mumford-Shah model

The Adaptive SOFM is hybridized with Mumford–Shah segmentation algorithm to detect edge and to represent boundary of segmented image. When a target image enters the neural network, the initial nodes of ASOFM are assigned randomly in the region whose intensity is less than the average. After Kohonen learning of nodes, the seeds of each node are assigned on a circle with radius, r. To update the seeds of each node, we employed Mumford-Shah criterion for evaluating the state of the image segmentation.

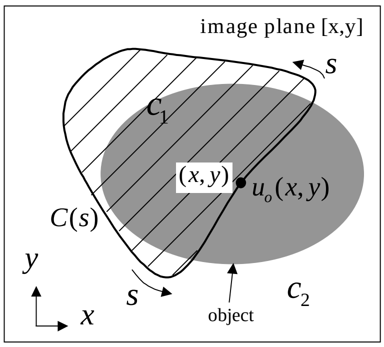


Figure 3. The schematic diagram of Mumford-Shah model

Figure 3 depicts the schematic diagram of Mumford-Shah model [4]. The model uses the statistical method to detect the boundary of image. The energy of Mumford-Shah model is defined as

$$E(C) = \lambda_1 \int_{inside(C)} \left| u_o - c_1 \right|^2 ds + \lambda_2 \int_{outside(C)} \left| u_o - c_2 \right|^2 ds \qquad (1)$$

where $u_o(x, y)$ is the intensity of image at a point (x, y), $C(s)$ is the boundary of segmented area, c_1, c_2 denote the average intensity of inside and outside of closed curve $C(s)$, s indicates the parameterizing axis and λ_1, λ_2 are the positive constants. By differentiating the equation (1) with respect to s, the energy $E(C)$ admits a global minimum in the image space.

$$\frac{\partial E(C)}{\partial s} = -\lambda_1 \cdot (u_o - c_1)^2 + \lambda_2 \cdot (u_o - c_2)^2 = 0 . \qquad (2)$$

However, this approach has significant drawbacks. The functional $E(C)$ is not intrinsic, since it depends on the parameter of s. We could obtain different solutions by changing the parameter while preserving the same initial curve. In practice, to solve the problem numerically we embed equation (2) into the dynamical scheme by making curve depending on an artificial parameter $t \geq 0$; that is, we solve the equation in $C(t, s)$ (with $C(0, s) = C(s)$),

$$\frac{\partial C(s)}{\partial t} = -\lambda_1 \cdot (u_o - c_1)^2 + \lambda_2 \cdot (u_o - c_2)^2, C(0, s) = C_o(s) \quad (3)$$

where $C_o(s)$ is a curve initially set, surrounding the object to be detected. To obtain the closed curve minimizing the energy in equation (3), the closed continuous curve C is represented by a discrete set of seeds. Applying this scheme to the whole nodes of ASOFM, each node makes a contour and the contour is described by discrete seeds. Figure 4 illustrates such a closed curve whose center is located at the node $\mathbf{n}_i$. Here, squares in black represent a set of seeds constituting the contour $C(s)$. The $C(s)$ is updated by the scheme of the Mumford – Shah model.

Based on Mumford-Shah criterion and conventional Kohonen network [7], the learning algorithm of ASOFM is derived as ;

Step 1) *Calculation of the average intensity of input image*:

Step 2) *Assigning and learning of Kohonen nodes*: According to Kohonen learning rule, all nodes are updated.

Step 3) *Initialization of seeds*: N_s discrete points are assigned for the seeds of each active node. The k th seed point of the i th node is denoted by $\mathbf{s}_{i,k}$.

Step 4) *Calculation of average intensities of points located inside and outside the closed curve, which are made by seeds:* The c_1 and c_2 of the closed curve made by seeds are calculated.

Step 5) *Sampling*: Draw a sample $\mathbf{x}(t)$ from the input distribution at time t.

Step 6) *Similarity matching*: Find the winning seed k^* at time t, using the minimum distance Euclidean criterion

$$k^* = \arg \min_{i,k} \left\| \mathbf{x} - \mathbf{s}_{i,k} \right\|, \mathrm{k} = 1, \cdots, N_s, \quad i = 1, \cdots N_c \qquad (4)$$

where $\| \cdot \|$ indicates the Euclidean norm, N_s and N_c indicate the number of seeds and the number of nodes respectively.

Step 7) *Node deleting and Seed updating*: If the distances between seeds and center are continuously decreasing to zero as time increases, the node is regarded as a dead node and is deleted. Otherwise, the winning seed and its neighbors are updated based on Kohonen learning.

$$\mathbf{s}_{i,k^*}(t+1) = \mathbf{s}_{i,k^*}(t) + \eta_1(t) \cdot (-\lambda_1 (u_o(\mathbf{s}_{i,k^*}(t)) - c_1)^2 + \lambda_2 (u_o(\mathbf{s}_{i,k^*}(t)) - c_2)^2) \cdot A(\mathbf{x} - \mathbf{s}_{i,k^*}(t)) \qquad (5)$$

$$\mathbf{s}_{i,k^*+1}(t+1) = \mathbf{s}_{i,k^*+1}(t) + \eta_2(t) \cdot (-\lambda_1 (u_o(\mathbf{s}_{i,k^*+1}(t)) - c_1)^2 + \lambda_2 (u_o(\mathbf{s}_{i,k^*+1}(t)) - c_2)^2) \cdot A(\mathbf{x} - \mathbf{s}_{i,k^*}(t)) \qquad (6)$$

$$\mathbf{s}_{i,k^*-1}(t+1) = \mathbf{s}_{i,k^*-1}(t) + \eta_2(t) \cdot (-\lambda_1 (u_o(\mathbf{s}_{i,k^*-1}(t)) - c_1)^2 + \lambda_2 (u_o(\mathbf{s}_{i,k^*-1}(t)) - c_2)^2) \cdot A(\mathbf{x} - \mathbf{s}_{i,k^*}(t)) \qquad (7)$$

where $\eta_1(t)$ and $\eta_2(t)$ are the learning coefficients of the winning seed and its neighbor, respectively and the function A is defined by

$$A(\mathbf{x} - \mathbf{s}_{i,k^*}(t)) = \exp\left(-\frac{\left\| \mathbf{x} - \mathbf{s}_{i,k^*}(t) \right\|^2}{\sigma^2}\right) . \qquad (8)$$

It makes the updating values of seeds are inversely proportional to $\left\| \mathbf{x} - \mathbf{s}_{i,k^*}(t) \right\|$.

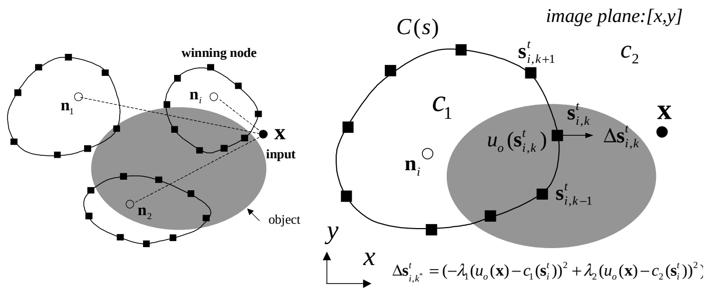
Step 8) *Nodes updating*: The location of each node is updated at the center of seeds.

$$\mathbf{n}_i(t) = \sum_{k=1}^{N_s} \mathbf{s}_{i,k}(t) / N_s \qquad (9)$$

where N_s is the number of seeds.

Step 9) *Continuation*: Continue with step 4 until no noticeable changes in the feature map are observed.

Step 10) *Merging segmented images:* After learning procedure, the segmented areas are merged.



(a) Selection of winning node, $\mathbf{n}_i$ (b) Learning of seeds, $\mathbf{s}^t_{i,k}$

Figure 4. Learning of seeds

4. RESULTS OF IMAGE SEGMENTATION

To investigate the performance of the proposed method, a synthetic and a real X ray image are tested. In our experiments, we choose the parameters as follows: $\lambda_1 = \lambda_2 = 0.0001$. The values of λ_1, λ_2 decide the updating value of seeds and are selected by trial and error method. Large values of λ_1, λ_2 accelerate the learning process but tend to make the dynamics of seeds unstable.

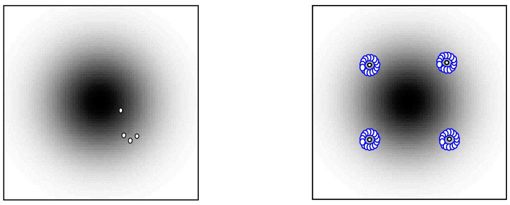
The learning rate of seed in equation (5) ~ (7), $\eta_1(t)$ is chosen to be 0.3 and that of neighbor, $\eta_2(t)$ is defined as $0.2\times(100-N)/100$ (N=iteration number). As the number of iteration increases, the learning rate of neighbor is decreased. The number of assigned node is determined according to image size, and the number of seeds for each node is set to 15. A large number of seeds need more computational time and a small number of seeds lack the representation ability of segmented image. We select all parameters by trial and error method.

4.1 Gaussian Image

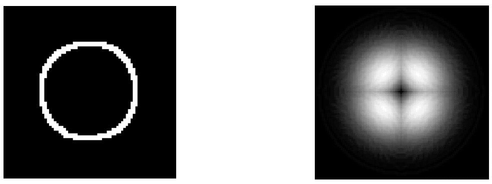
Figure 5 (a) shows a synthetic image whose intensity distribution bears gaussian distribution. That is defined as,

$$u_o(x,y) = 255\cdot[1-\exp(\frac{-(x-50)^2-(y-50)^2}{20^2})]. \qquad (10)$$

To solve this segmentation problem, we assign randomly 4 nodes at image space. Figure 5 (a) shows the target image and its initial nodes. The initial nodes are updated by Kohonen learning. By the learning, the nodes are spread through out the object part. After Kohonen learning, the initial seeds are assigned along a small circle as shown in Figure 5 (b). From equation (4), the winning seed is selected for each input $\mathbf{x}$. Then, the winning seed and its neighbor are updated by equations (5)~(7). Figure 5 (c) shows the segmentation results after 30 iterations. The small circles in figure are the assigned seeds. Figure 5 (d) shows the segmented image by Sobel operator, in which the white part of image indicates the edge. It can be seen that the Sobel can not detect the edge while the proposed method shows a good performance.



(a) image and initial nodes (b) initial seeds

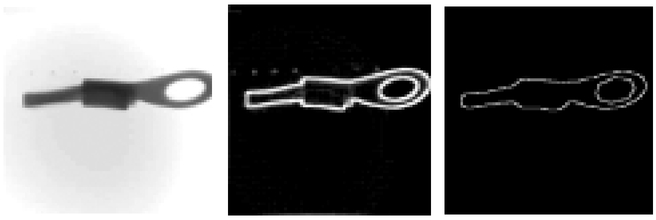


(c) segmented image of the proposed algorithm (d) segmented image of the Sobel operation

Figure 5. The segmentation result of a circle image (image : 100 × 100)

4.2 An X ray Image: An Electrical Connector

Figure 6 (a) shows an X ray image of an electrical connector. In the image, the lower intensity means longer transmitted distance or high density of object. Figure 6 (b) is the edge image obtained by the Sobel operation. Figure 6 (c) is the segmentation result of the proposed method. The procedure of segmentation is the same as that discussed in the previous example. By comparing two results, we can see that the proposed algorithm shows much better segmentation result in the sense that it can describe the object with more accuracy.



(a) the connector (X ray image) (b) the Sobel operation (c) the proposed algorithm

Figure 6. The segmentation of X ray transmitted connector image (image: 256×256)

5. CONCLUSIONS

The X ray image has the inherent properties of vagueness and blur in the boundary region and thus, it is difficult to detect edge or segment object region by conventional image processing algorithm. In this paper, a neural network based image segmentation method using a self organizing feature map was proposed for X ray image. The proposed method uses the Mumford-Shah model to detect the edge of an X ray image and uses the adaptive self organizing feature map to represent the segmented area in image. To verify the performance of proposed algorithm, we tested synthetic image and an X ray image of an electrical connector. The simulation studies showed that the proposed method improves a good ability of segmentation of X ray image, which can not obtained by Sobel operator. This implies that the proposed method can be applied to other X ray images having similar image characteristics presented here.

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