Segmentation of Mammography Images Using Kohonen Self-Organizing Feature Maps

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Abstract

Breast cancer is the second leading cause of cancer mortality in women. Mammography remains the best method for early detection of cancers of the breast, capable of detecting small lumps up to two years before they grow large enough to be palpable on physical examination. X-ray images of the breast must be carefully evaluated to identify early signs of cancerous growth. Segmenting, or partitioning, radiographic images into regions of similar texture is often performed during the process of image analysis and interpretation. The relative lack of structure definition in mammographic images and the subtle transition from one texture to another makes segmentation extremely difficult. The task of classifying different texture regions can be considered a form of exploratory analysis, since a priori knowledge about the number of different regions in the image is generally not known. This paper presents a preliminary examination of an image segmentation technique based on the Kohonen Self-Organizing Feature Map (SOM). The SOM network lends itself well to this problem for two reasons. First, such a network can be trained to recognize and classify regions exhibiting similar internal structure. It learns in an unsupervised mode, requiring no a priori knowledge about the number or nature of regions to be classified. Another important feature of the SOM is its topology-preserving behavior. The competitive learning algorithm employed by the network ensures that regions close together in the input space will maintain their relative proximity in the output space. This order-preserving characteristic of the SOM makes makes it a good candidate for spatially-oriented problems such as image segmentation. The choice of node number for the competitive layer determines the maximum number or classes into which image regions can be partitioned. This paper presents a method of region classification using a simple SOM network and explores the effect varying the number of neurons in the competitive layer has on the resulting segmented image.

Introduction

According to the American Cancer Society, breast cancer is second only to lung cancer as the most prevalent type of cancer afflicting women, but remains the leading cause of cancer death in women between the ages of 40 and 55. This year in the United States, approximately 180,200 women will be diagnosed with invasive breast cancer. During the same year, about 44,190 women will lose the fight against this deadly disease. Although the incidence of new breast cancer rose on average 4 percent between the years 1982 and 1987, the incidence rate has tapered off to just over one percent in the years since. Much of this welcome decrease in new breast cancer diagnoses has been attributed to the increased use of mammography to detect early stages of this disease. Although significant advances have been made in the technology of mammography, much work remains to be done to improve overall detection accuracy.

Segmenting a mammographic image into homogeneous texture regions representing disparate tissue types is often a useful preprocessing step in the computer-assisted detection of breast cancer. Whereas other medical imaging modalities, such as lung x-rays, exhibit a high degree of structural definition and regularity, the same cannot be said for radiographic images of the breast. These images typically possess diffuse, cloud-like patterns lacking regular structural patterns. Various segmentation techniques have been proposed based on statistically measurable features in the image (Duda & Hart 1973). Clustering algorithms, such as K-means and ISODATA, operate in an unsupervised mode (i.e. do not require labeled data) and have been applied to a wide range of classification problems (Tou & Gonzalez 1974). (Chen & Kundu 1994) proposed an unsupervised texture segmentation method based on hidden Markov models. (Panjwani & Healey 1995) and (Uchiyama & Arbib 1994) discuss the application of Markov random fields and competitive learning techniques, respectively, for segmenting color texture images. (Pemmaraju 1995) discusses a neuro-fuzzy classification scheme for segmenting cervical images. The image understanding potential of Kohonen SOM's as applied to identifying heart contours in emission tomography is discussed in (Manhaeghe *et al.* 1994).

Another medical application of self-organizing neural networks which has been explored is the classification of benign vs. malignant tissue in ultrasound images of the prostate gland (Kotropoulos *et al.* 1994). In general, these segmentation techniques either process image data directly based on pixel intensity or generate a set of features which serve as the basis for further classification and segmentation.

The method proposed in this article uses a Kohonen Self-Organizing Feature Map to partition regions having dissimilar textural characteristics. The network learns to discriminate between regions exhibiting different textural characteristics using Kohonen's unsupervised learning rule. Although distinct boundaries are difficult to identify, the network eventually defines a boundary between two adjacent regions having different intensity patterns. The neighborhood characteristics of two pixels in the same region of the image will tend to be more closely related than those of two pixels located farther apart. The network essentially clusters pixels belonging to similar neighborhoods into the same class or region (Dayhoff 1996).

Perhaps the main strength of the SOM approach to image segmentation is its topology-preserving behavior (Villmann *et al.* 1997). The network uses a vector quantization approach to iteratively assign each input pattern to the closest matching codebook vector (i.e. cluster center). Through competitive learning, pixels in the same neighborhood (i.e. belonging to the same underlying structure) will tend to be classified by the same neuron in the competitive layer (Rumelhart *et al.* 1988). As input patterns are presented to the network over many epochs, the network begins to self-organize and delineate boundaries between statistically dissimilar regions. In effect, the network is performing a clustering function as it attempts to minimize the mean squared error between each pixel and its cluster center. From a physiological standpoint, the network creates a map reminiscent of the retinotopic map identified in the visual cortex (Kohonen 1987).

Methodology

Image Preprocessing

A 256 x 256 pixel-wide region of interest (ROI) having significant visual texture variation is selected for classification and segmentation. The ROI is first processed with a median filter using a 3 x 3 convolution kernel to reduce the image noise level. Since texture is determined by pixels located in close proximity, the network will be trained to recognize specific intensity patterns within a narrow 9 x 9 pixel neighborhood. This 9 x 9 cluster of pixels defines the network's receptive field. The filtered image is then transformed into a stack of input pattern vectors by scanning the image in a raster fashion (e.g. top left to bottom right) and reshaping each 9 x 9 neighborhood of pixels into a 81 x 1 vector. This ordered transformation from image matrix to input vector format ensures the spatial relationship between two adjacent neighborhoods in the original image is maintained, enabling the network to exercise its topology-preserving behavior. The matrix of input pattern vectors therefore has the dimensions 81 x 61504 pixels for the 256 x 256 image ROI.

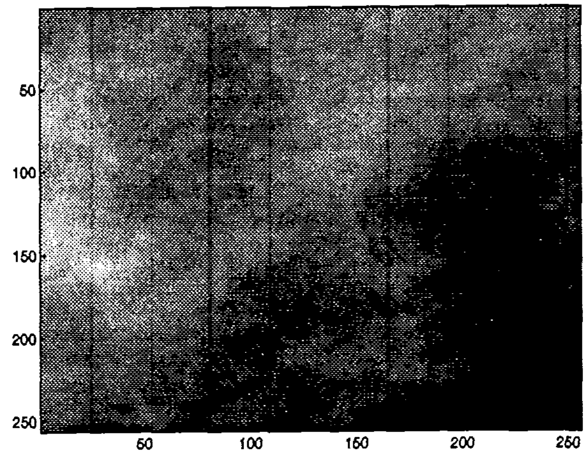

Figure 1: Original Mammogram ROI

Network Architecture and Training

A conventional Kohonen self-organizing network is used to simulate unsupervised learning of the different homogeneous texture regions in the input image. The 81 neurons in the network's input layer correspond to the 81 pixels comprising each input pattern vector. Each input neuron, in turn, is fully connected to each neuron in the competitive layer. The number of neurons in the competitive layer determines the maximum number of partitions into which the image can be segmented. Network weights are initialized based on the statistical grayscale values of the original image pixels.

The network is then trained to recognize similarities in the input vectors using Kohonen's training rule (Kohonen 1987). In competitive learning, each neuron in the competitive layer competes for the right to respond to the current input pattern vector. The neuron whose weights give the strongest response when multipled by the input vector wins the competition. The winning neuron's weights (and those of its neighbors) are then updated in the direction of the current input pattern vector. This weight update process makes it more likely the winning neuron will win in the future when presented a similar input pattern. During the learning process, the size of the neighborhood updated each time decreases, and each winning neuron learns to discriminate between its specific pattern class and all others.

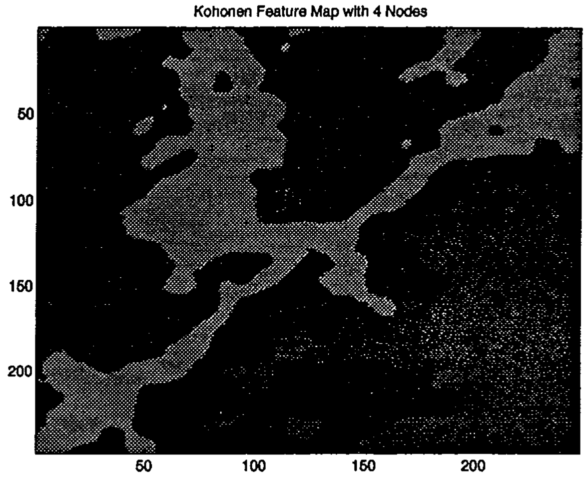

Figure 2: Kohonen Feature Map [4 Nodes in Competitive Layer]

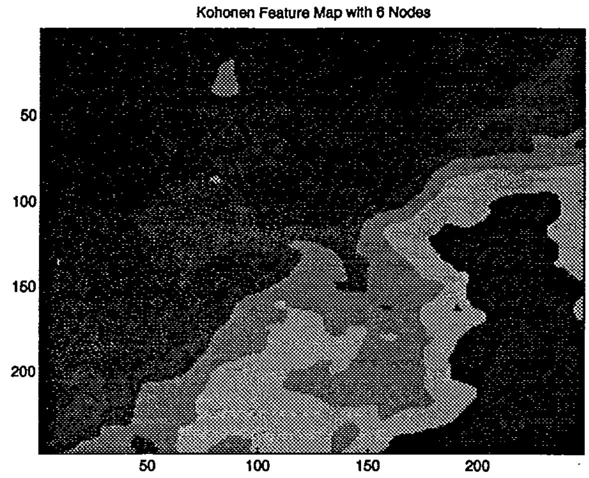

Figure 3: Kohonen Feature Map [6 Nodes in Competitive Layer]

Experimental Results

The original 256 x 256 ROI taken from a representative mammogram is shown in Figure 1. Note the absence of any well-defined boundaries in the image. Ideally we want the network to partition the image into highly homogeneous regions. The neural network was initialized using minimum and maximum intensity values for each input pattern vector. The image to be segmented was transformed to the appropriate column vector matrix and presented to the network. The network was trained with 4, 6, 8, 10, 12, and 20 nodes in the competitive layer. Training for each trial took place over 10,000 epochs. Network weights were reinitialized each time the number of neurons in the competitive layer was modified. The MatLab neural network toolbox version 4.2c software package was used to implement the SOM.

Figures 2-7 depict classification results using 4, 6, 8, 10, 12, and 20 neurons in the competitive layer. Pixels in the same grayscale band have been assigned to the same class by the neural network. Two non-adjacent regions need not be significantly different, just different enough that the network can infer a change in textural characteristics between the two regions. At some point, the network decides that the current input pattern vector correlates more closely with a neighboring neuron (codebook vector), creating a boundary condition. It is encouraging to note that region integrity is maintained as one views the image from top to bottom, although input patterns were presented to the network in a left to right, top to bottom scan. This result validates the claim that the Kohonen feature map is topology preserving. As expected, the number of regions identified is equal to the number of competitive layer neurons available to make the assignment.

The effect achieved by systematically adding more neurons to the competitive layer can be seen directly from the figures. Each additional neuron generates another class the network can use to define a new partition. In other words, increasing the number of competitive neurons in turn increases the network's level of resolution; pixels assigned to the same region in one image ($neurons_{k-1}$) may be split up into different classes in the next higher resolution image ($neurons_k$). This effect can be seen if we compare Figure 3 with Figure 4. Notice how the central pixels comprising the dark region at the bottom right corner of the first image are further segmented into another region corresponding to lower intensity values.

At some point, adding more neurons can lead to a state of diminishing returns. Adding too many output nodes may result in overclassification; pixels that should have been assigned to the same cluster are now split into two or more different texture regions. Figure 7 demonstrates the effect using 20 nodes has on segmentation. Previous divisions of dissimilar regions have degenerated into a fragmented association of clusters. This points out the basic challenge unsupervised segmentation presents: the optimal number of neurons is generally not known a priori and must be learned heuristically. In short, too few neurons in the competitive layer will underclassify (blur) an image, while too many will overclassify (fragment).

A important observation to be made is that the addition of new neurons does not disturb the overall boundary relationships defined at the previous level. In other words, each successive partitioning results in a topology that remains true to the underlying structure the segmentation process is trying to capture. This aspect of the SOM network has significant implications for its application as a segmentation tool in image processing. For example, by varying the number of nodes we can gain an understanding of both global and local image characteristics.

As a final demonstration of the SOM's ability to segment difficult to read medical images, consider Figure 8. This figure shows a 256 x 256 ROI with a rather large tumor in the left central portion of the image. The subtle texture changes as normal tissue gives way to the tumor mass render the tumor difficult to detect, let alone segment away from the surrounding normal tissue. To evaluate the ability of the SOM to detect such a tumor by assigning pixels inside and outside the mass to different classes, we used a 8-neuron competitive SOM in the exact same manner as described to segment the normal ROI in Figure 1. The segmentation result is shown in Figure 9. Whereas the tumor blended in well with the surrounding normal tissue in the original image, it stands out clearly in the classified image.

Conclusion

This work presents a preliminary look at a SOM-based image segmentation technique. The power of this approach lies both in its simplicity and generality. As a tool for image discovery, unsupervised learning techniques make no a priori assumptions about the number or type of textural regions an image might contain. A poor choice for the size of the competitive layer may lead to unsatisfactory partitioning. One advantage of the competitive-learning approach is that the network may do a better job seeking out hidden structure than initial classification assumptions could have provided. Medical image analysis is often conducted with little understanding of the underlying data relationships.

Although no formal metric was applied to evaluate how well the network segmentation maps correspond to actual tissue distributions, a visual inspection of the segmented image clearly shows a high degree of correlation between the intensity regions in the original image and the regions constructed in the segmented image. Additional research using ground truth data generated by a radiologist is needed to evaluate exactly how well the segmented tumor correlates to the expert's judgment of where the boundary between tumor and normal tissue lies. This approach merits further study and comparison with other segmentation techniques to gain a better understanding of its strengths and limitations as an image segmentation tool.

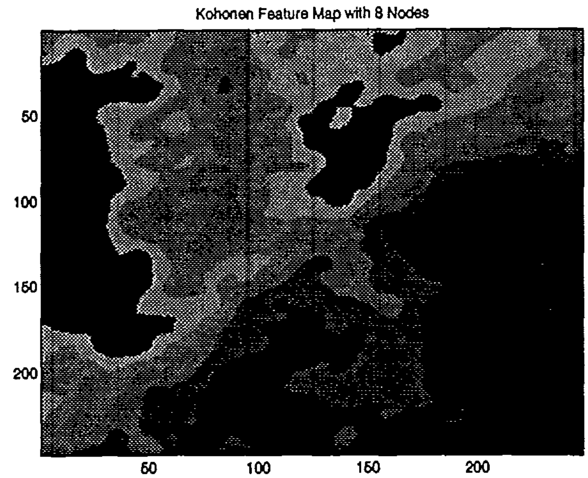

Figure 4: Kohonen Feature Map [8 Nodes in Competitive Layer]

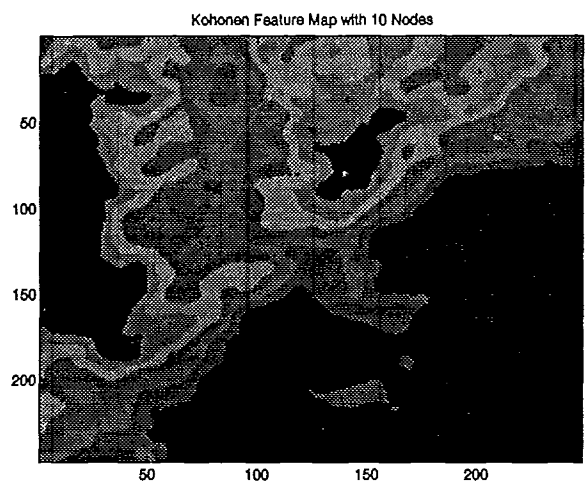

Figure 5: Kohonen Feature Map [10 Nodes in Competitive Layer]

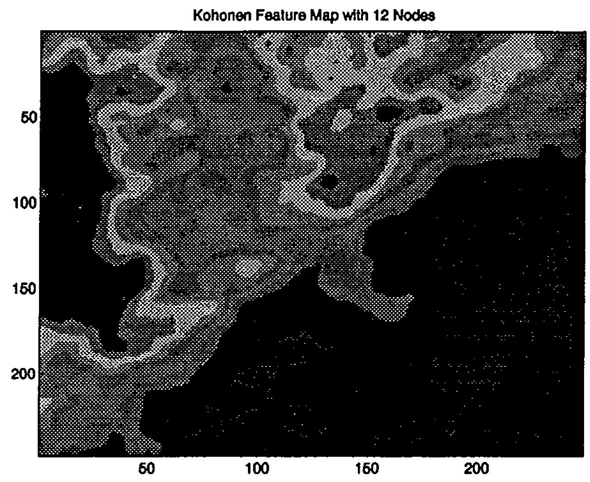

Figure 6: Kohonen Feature Map [12 Nodes in Competitive Layer]

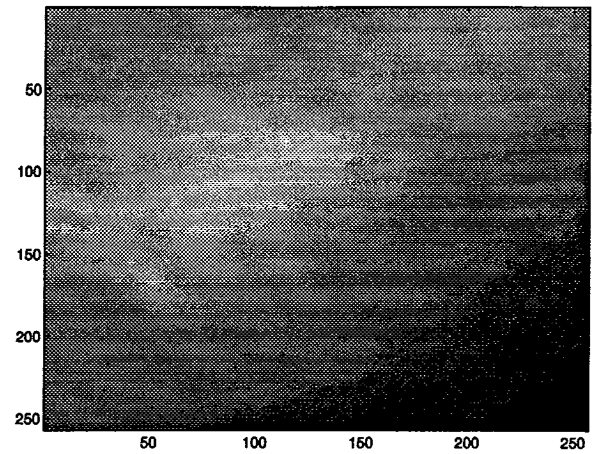

Figure 8: Mammogram ROI [Embedded Tumor]

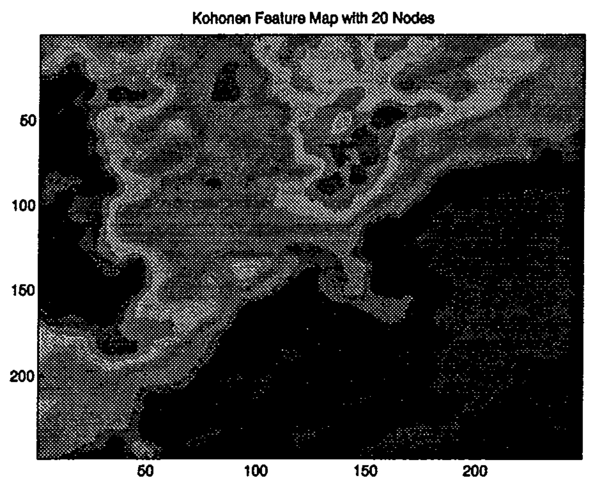

Figure 7: Kohonen Feature Map [20 Nodes in Competitive Layer]

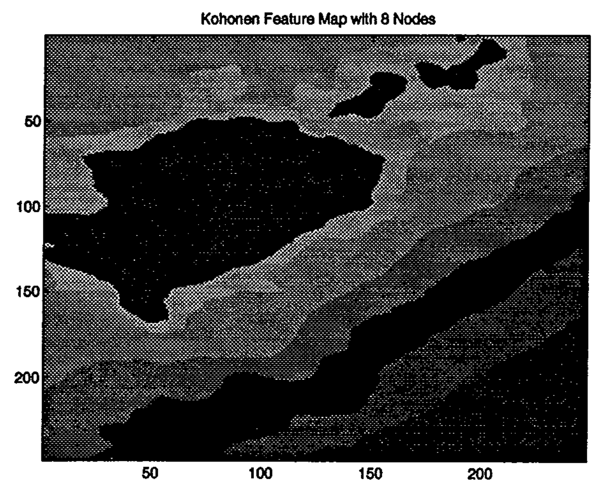

Figure 9: Kohonen Feature Map [8 Nodes in Competitive Layer]

References

Chen, J., and Kundu, A. 1994. Unsupervised texture segmentation using multichannel decomposition and hidden markov models. *IEEE Transactions on Image Processing* 4(5):603–619.

Dayhoff, J. 1996. *Neural Network Architectures: An Introduction.* International Thomson Computer Press.

Duda, R., and Hart, P. 1973. *Pattern Classification and Scene Analysis.* John Wiley and Sons, Inc.

Kohonen, T. 1987. *Self-Organization and Associative Memory.* Springer-Verlag.

Kotropoulos, C.; Magnisalis, X.; Pitas, I.; and Strintzis, M. 1994. Nonlinear ultrasonic image processing based on signal-adaptive filters and self-organizing neural networks. *IEEE Transactions on Image Processing* 3(1):65–77.

Manhaeghe, C.; Lemahieu, I.; Vogelaers, D.; and Colardyn, F. 1994. Automatic initial estimation of the left ventricalar myocardial midwall in emission tomograms using kohonen maps. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 16(3):259–266.

Panjwani, D., and Healey, G. 1995. MRF models for unsupervised segmentation of textured color images. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 17(10):939–954.

Pemmaraju, S.; Mitra, S.; Shieh, Y.; Roberson, G. 1995. *Segmentation of radiographic cervical images with neuro-fuzzy classification of multiresolution wavelets.* Proceedings of SPIE Medical Imaging '95: Image Processing.

Rumelhart, D.; McClelland, J.; ; and the PDP Research Group. 1988. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition.* The MIT Press.

Tou, J., and Gonzalez, R. 1974. *Pattern Recognition Principles.* Addison-Wesley Publishing Company.

Uchiyama, T., and Arbib, M. 1994. Color image segmentation using competitive learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 16(12):1197–1206.

Villmann, T.; Der, R.; Herrmann, M.; and Martinetz, T. 1997. Topology preservation in self-organizing feature maps: Exact definition and measurement. *IEEE Transactions on Neural Networks* 8(2):256–266.