MULTISCALE SEGMENTATION THROUGH A RADIAL BASIS NEURAL NETWORK

Xuli Zong†, *Anke Meyer-Baese*‡, *and Andrew Laine*†

†Department of Computer and Information Science and Engineering
&
‡Department of Electrical and Computer Engineering
University of Florida, Gainesville, FL 32611
E-mail: zxl@cise.ufl.edu, anke@alpha.ee.ufl.edu, and laine@cise.ufl.edu

ABSTRACT

This paper presents an approach for image segmentation using sub-octave wavelet representations and a dynamic resource-allocating neural network. The algorithm is applied to identify regions of masses in mammographic images of varied degrees of perceptual difficulty. Each mammographic image is first decomposed into overcomplete wavelet representations of sub-octave frequency bands. A feature vector for each pixel through the scale space is constructed from fine to coarse scales. The feature vectors are used to drive a neural network classifier of dynamic resource allocation for segmentation.

Sub-octave wavelet representations have an improved capability of characterizing subtle (band-limited) features frequently seen in mammographic images. A radial basis network of dynamic resource allocation is shown to have better adaptation and generalization in a redundant feature space. Experimental results along with statistical analysis are partially compared to a traditional classifier.

1. INTRODUCTION

Dyadic wavelet transforms have been widely used for analysis of many non-stationary signals and images [1, 2, 3, 4, 5, 6, 7, 8]. Overcomplete (redundant) representations can be shift-invariant, a desirable property for problems in pattern recognition [9]. The traditional DWT is an octave-based transformation where scales increase as powers of two [2]. However, sometimes the best representation of a signal's details may exist between two consecutive levels of scale within a DWT [10]. To more reliably identify features through scale space, we carry out a sub-octave wavelet transform previously developed in [11, 12, 13]. As suggested and first proposed by Daubechies [11], a sub-octave wavelet transform provides a means to represent details within sub-octave frequency bands (voices) which are equally-spaced divisions of an octave band.

Mammographic image enhancement can improve visibility of unseen or barely seen breast cancers [14]. To locally enhance possible masses in mammograms, we first identify regions of support for each possible lesion. In this paper, an image segmentation algorithm is developed to estimate and identify areas of lobular and spicular lesions. A sub-octave wavelet transform [12, 13], a generalization of the dyadic wavelet transform [2], is used for analysis and feature representation. Neural network techniques have been used in function interpolation, image restoration, and texture segmentation [15, 16, 17, 18]. In our algorithm, we adopt and extend a resource-allocating neural network for segmentation of small subtle masses in digitized mammograms.

The remainder of this article is organized as follows. In Section 2, we present the methodology employed in our algorithm for multiscale segmentation. We first describe sub-octave wavelet representations and a radial basis neural network of dynamic resource-allocation. We then present the algorithm for image segmentation. Section 3 shows several experimental results. Statistical analysis of test results on a set of randomly selected sample images with masses from a mammographic database are also presented. Finally, the paper is concluded in Section 4.

2. METHODOLOGY AND ALGORITHM FOR MULTISCALE SEGMENTATION

Most segmentation methods can be roughly divided into two major steps: feature extraction and classification [19]. In this section we describe our approach for multiscale image segmentation. We develop a sub-octave wavelet representation based method for feature

0-8186-8183-7/97 $10.00

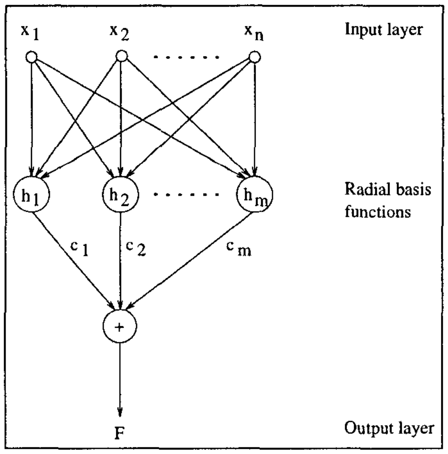


Figure 1: Network architecture, a three-layer resource-allocating neural network of radial basis functions.

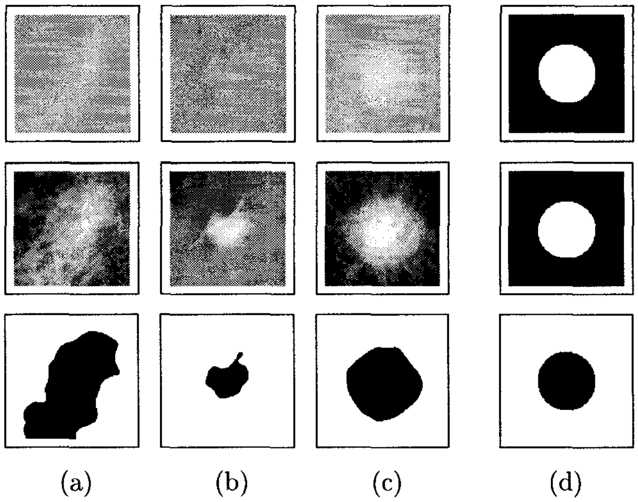


Figure 2: Test Images. First row: original ROI images; Second row: smoothed and enhanced images; Third row: ideal segmentation results. Columns: (a-c) real mammograms, (d) a mathematical model.

extraction and carry out feature classification via a radial basis network.

2.1. Sub-Octave wavelet representations

Sub-Octave wavelet representations [11, 12, 13] have shown advantages over dyadic wavelet representations for characterizing band-limited features, such as texture [20]. An M-sub-octave wavelet transform of a 1-D function $f(x) \in L^2(\boldsymbol{R})$ is defined as

$$W_j^m f(x) = f * \psi_{2^j}^m(x), \tag{1}$$

where $\psi_{2^j}^m(x) = \frac{1}{2^j}\psi^m(\frac{x}{2^j})$ is the dilation of the m-th basis wavelet $\psi^m(x)$, at scale 2^j, $m = \{1, 2, ..., M\}$, and $j \in Z$. Scaling approximation $S_j f(x)$ at level j (scale 2^j) can be defined as

$$S_j f(x) = f * \varphi_{2^j}(x), \tag{2}$$

where $\varphi_{2^j}(x) = \frac{1}{2^j}\varphi(\frac{x}{2^j})$ is a scaling function dilated at scale 2^j. A 1-D sub-octave wavelet transform can be easily extended to 2-D and implemented using FIR filters [11, 12, 13]. Feature extraction is accomplished by processing and combining information from each sub-octave frequency band. A feature vector (pattern) is denoted as

$$\mathbf{p}(x) = (p_1(x), p_2(x), p_3(x), ..., p_L(x)), \quad L = J \times M + 1,$$

where J and M are selected values for a J-level M-sub-octave wavelet transform, L is the length of a feature vector, and x is a pixel spatial location. Element $p_k = w_k\, g(W_j^m f(x))$ where $1 \leq k < L$, $k = (j-1)M + m$, and w_k is a parameter (weight factor) and $g()$ may be a function, such as thresholding. Finally, element $p_L = w_L\, g(S_J f(x))$ where $S_J f(x)$ is the coarse scale approximation of $f(x)$.

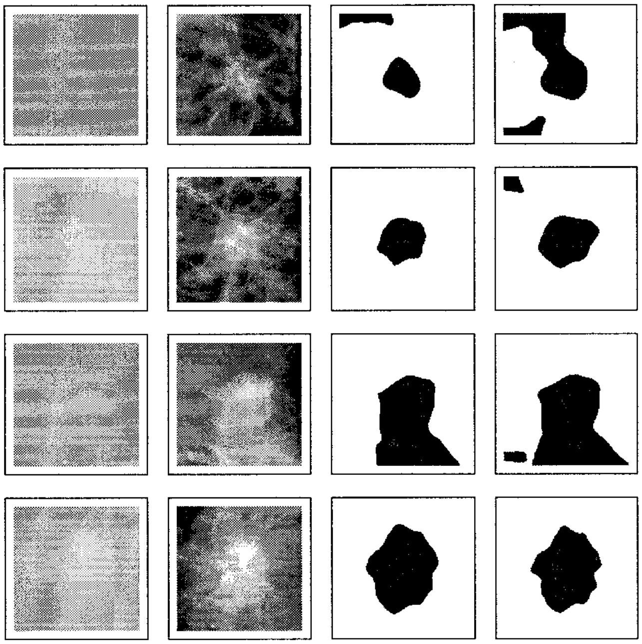
2.2. Resource-allocating neural networks

The neural network used for segmentation is a resource-allocating neural network having a three-layer architecture as described in [15]. It allocates a new computational unit whenever an unusual pattern is presented to the network shown in Figure 1. This network forms compact representations, yet learns easily and rapidly. The network can be used at any time in the learning process and the learning patterns do not have to be repeated. The units in this network respond to only a local region of the space of its input values.

The network learns by allocating new units and adjusting the parameters of the existing units. If the network performs poorly on a presented pattern, then a new unit is allocated in an attempt to correct the response to the presented pattern. If the network performs well on a presented pattern, then the network parameters are updated using the standard method of LMS gradient descent.

2.3. Overall Algorithm

Image segmentation using texture information has been applied previously [21, 22, 23, 24, 20]. Such methods perform best when texture information is a discriminating factor among different regions of interest in an image. In comparison to edge-based approaches for object detection [25], this method is a region-based image segmentation algorithm relying upon multiscale representations. Segmentation consists of four major steps. The first step is to preprocess an image for smooth-



(a) (b) (c) (d)

Figure 3: Experimental results of image segmentation. Four test cases, one each row, are shown. The first column (a) is an original image, column (b) is smoothed and enhanced images, column (c) is the segmented result, and column (d) is the result of a traditional statistical classifier.

ing noise and enhancing low spatial-frequency features for segmentation [12]. The second step is feature extraction, which is done through transforming an image ROI into sub-octave spatial frequency bands. Next feature vectors are constructed and used to drive a neural network classifier for image segmentation. Finally we postprocess the segmented regions obtained to remove isolated noise segments.

3. EXPERIMENTAL RESULTS

In this study, we first test the network classifier for its adaptation and generalization in the feature space with simple experiments. Several cropped images (regions of interest, ROI) were used to train and/or test the neural network for segmentation performance. These experiments produced promising preliminary results. Sample training and test images are shown in Figure 2, where the first row shows original ROI's, the second row show smoothed and enhanced versions, the third row presents "ideal" segmentation results for each image obtained by hand of a radiologist specializing in mammography. These data provided a "gold standard". Several test images have been used to test the neural network trained through the three patterns. Figure 3 shows experimental results of mass segmentation within cropped regions. There are four displays for each test image. The first is an original, the second is a smoothed and enhanced version, the third shows the segmented result. The fourth column is the result of a statistical classification based on local mean and standard deviation, shown here for comparison. An improvement is quite visible for the segmented results produced from our algorithm.

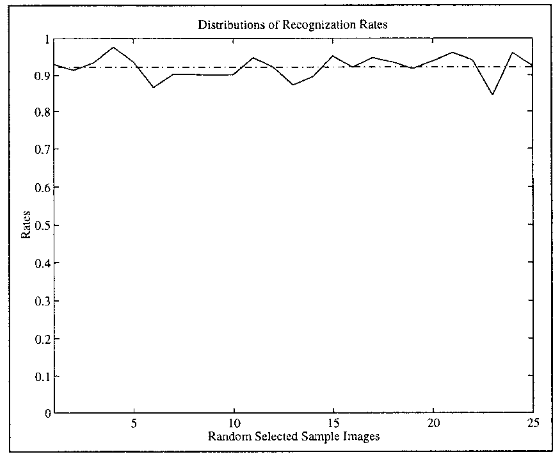


Figure 4: The distribution of recognition rates from the segmentation algorithm when tested on a set of sample images.

Next, we show statistical analysis of the test results on a set of randomly selected sample images containing subtle masses from a mammographic database. The preliminary experimental results reported here are from an on-going research effort. For the study, we choose a set of test images consisting of 25 randomly selected sample images from 120 images, containing $0 - 2cm$ masses in a local mammographic database. The masses in the database have varied degrees of perceptual difficulty. Figure 4 shows the distribution of the algorithm's recognition rates when tested on the set of 25 sample images. The mean recognition rate was 92.2%. The standard deviation of the recognition rates was 3.12%. We obtained maximum and minimum recognition rates 97.67% and 84.47%, respectively.

4. CONCLUSIONS

In this paper, we have presented a new algorithm for segmentation of subtle masses in mammograms. We utilized sub-octave wavelet representations for parameterized feature extraction and adopted a radial basis neural network of dynamic resource allocation for feature classification. The method suggests improved results when tested on subtle masses typical in mammograms compared with a statistical classifier based on local mean and standard deviation. Statistical analysis of experimental results on a set of 25 randomly selected sample images containing masses with varied visibility was also presented. A future direction of this research shall include testing the method on larger data sets of training samples to determine stability and clinical performance.

5. ACKNOWLEDGMENTS

The authors gratefully acknowledge Sergio Schuler and Barbara Steinbach for compiling the local database.

6. REFERENCES

[1] S. Mallat and W. L. Hwang, "Singularity detection and processing with wavelets", *IEEE Transactions on Information Theory*, vol. 38, no. 2, pp. 617–643, 1992.

[2] S. Mallat and S. Zhong, "Characterization of signals from multiscale edges", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 7, pp. 710–732, 1992.

[3] J. Lu, J. B. Weaver, D. M. Healy Jr., and Y. Xu, "Noise reduction with multiscale edge representation and perceptual criteria", in *Proceedings of IEEE-SP International Symposium on Time-Frequency and Time-Scale Analysis*, Victoria, B.C., 1992, pp. 555–558.

[4] J. Lu and D. M. Healy Jr., "Contrast enhancement of medical images using multiscale edge representation", in *Wavelet Applications,* Proceedings of SPIE, Orlando, FL, 1994, vol. 2242, pp. 711–719.

[5] A. F. Laine, J. Fan, and S. Schuler, "Contrast enhancement by dyadic wavelet analysis", in *Proceedings of the 16th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Baltimore, MD, 1994, vol. 1, pp. 10a–11a.

[6] A. Laine, J. Fan, and W. Yang, "Wavelets for contrast enhancement of digital mammography", *IEEE Engineering in Medicine and Biology Magazine,* vol. 14, no. 5, pp. 536–550, 1995.

[7] X. Zong, A. F. Laine, E. A. Geiser, and D. C. Wilson, "De-noising and contrast enhancement via wavelet shrinkage and nonlinear adaptive gain", in *Wavelet Applications III,* Proceedings of SPIE, Orlando, FL, 1996, vol. 2762, pp. 566–574.

[8] D. Wei and C. S. Burrus, "Optimal wavelet thresholding for various coding schemes", in *Proceedings of ICIP,* Lausanne, Switzerland, 1996, vol. I, pp. 610–613.

[9] M. Vetterli and J. Kovačević, *Wavelets and Subband Coding,* Prentice Hall, Englewood Cliffs, NJ, 1995.

[10] A. Laine, W. Huda, D. Chen, and J. Harris, "Segmentation of masses using continuous scale representations", in *Digital Mammography '96, Proceedings of the 3rd International Workshop on Digital Mammograph,* K. Doi, M. L. Giger, R. M. Nishikawa, and R. A. Schmidt, Eds., Chicago, IL, 1996, pp. 447–450, Amsterdam, The Netherlands: Elsevier.

[11] I. Daubechies, *Ten Lectures on Wavelets,* Number 61 in CBMS-NSF Series in Applied Mathematics. SIAM, Philadelphia, Pennsylvania, 1992.

[12] A. F. Laine and X. Zong, "A multiscale sub-octave wavelet transform for de-noising and enhancement", in *Wavelet Applications in Signal and Image Processing IV,* Proceedings of SPIE, Denver, CO, 1996, vol. 2825, pp. 238–249.

[13] A. F. Laine and X. Zong, "Feature enhancement with noise suppression via multiscale sub-octave wavelet analysis", *submitted to Medical Image Analysis*, 1997.

[14] A. F. Laine, S. Schuler, J. Fan, and W. Huda, "Mammographic feature enhancement by multiscale analysis", *IEEE Transactions on Medical Imaging*, vol. 13, no. 4, pp. 725–740, 1994.

[15] John Platt, "A ressource-allocating network for function interpolation", *Neural Computation*, vol. 3, pp. 213–225, 6 1991.

[16] M. Musavi and W. Ahmed, "On the training of radial basis function classifiers", *Neural Networks*, vol. 5, no. 4, pp. 595–603, 1992.

[17] W. Qian and L. P. Clarke, "Wavelet-based neural network with fuzzy-logic adaptivity for nuclear image restoration", *Proceedings of the IEEE*, vol. 84, no. 10, pp. 1458–1473, 1996.

[18] J. Mao and A. K. Jain, "A self-organizing network for hyperellipsoidal clustering (HEC)", *IEEE Transactions on Neural Networks*, vol. 7, no. 1, pp. 16–29, 1996.

[19] M. Nadler and Eric P. Smith, Eds., *Pattern Recognition Engineering*, John Wiley & Sons, Inc., New York, NY, 1993.

[20] A. Laine and J. Fan, "Frame representations for texture segmentation", *IEEE Transactions on Image Processing*, vol. 5, no. 5, pp. 771–780, 1996.

[21] M. Kardan J. M. H. DU Buf and M. Span, "Texture feature performance for image segmentation", *Pattern Recognition*, vol. 23, pp. 291–309, 1990.

[22] A. K. Jain and F. Farrokhnia, "Unsupervised texture segmentation using gabor filters", *Pattern Recognition*, vol. 24, no. 12, pp. 1167–1186, 1991.

[23] A. C. Bovik, "Analysis of multichannel narrowband filters for image texture segmentation", *IEEE Transactions on Signal Processing*, vol. 39, pp. 2025–2043, Sept. 1991.

[24] J. C. Bezdek, L. O. Hall, and L. P. Clarke, "Review of MR image segmentation techniques using pattern recognition", *Medical Physics*, vol. 20, no. 4, pp. 1033–1048, 1993.

[25] A. Laine and X. Zong, "Border identification of echocardiograms via multiscale edge detection and shape modeling", in *Proceedings of ICIP*, Lausanne, Switzerland, 1996, vol. III, pp. 287–290.