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SAR IMAGE CLASSIFICATION USING SUPERVISED NEURAL CLASSIFIERS

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Abstract. An investigation about four supervised neural classifiers based on the Minkovski-r error and the modified Fisher criterion is evaluated to classify a double textured SAR amplitude image. Regions around pre-classified pixels are presented to train the neural network that learns a sub-optimal set of masks via back-propagation algorithm. Classification performance is evaluated using kappa statistics. The neural classifiers showed almost the same performance for different window mask sizes and training samples. However, the Minkovski-r=1.1 error showed a slightly better performance than the others. Best results are obtained when the neural classified image is followed by an erosion process via Median filter. The results outperformed the classification performance of two statistical classifiers: the Minimum Bayes error and the Kullback-Liebler distance.

Keywords: SAR, neural networks, classification, back-propagation, Minkovski error, Fisher criterion.

1. Introduction

Artificial neural networks (ANN) algorithms has been increasingly applied to remote sensing for image classification in the last years, as indicated by classical papers such as Benediktsson et. al. (1990), Bischof et al. (1992), Hara et al. (1994) and Chen et al. (1996). The Synthetic Aperture Radar (SAR) is a microwave active imagery system that has been largely used due to its possibility of day-and-night operation in almost all-weather conditions. According to Oliver and Quegan (1998), the SAR system generates images by the coherent processing of the scattering signals, so the resulting scene texture has an undesired multiplicative speckled noise that reduces drastically the ability to distinguish the features of the classes. The rejection of the speckle noise motivated many works where ANN algorithms has been applied to SAR imagery classification, such as Ghinelli and Bennett (1997), Ito and Omatu (1998), Tzeng and Chen (1998), Frate and Lichtenegger (1999), Gedira et al. (2000) and Jacob et al (2002).

According to Hara et al. (1994) and Gedira et al. (2000), the rapid increase of ANN applications in remote sensing imagery classification is due mainly to their ability to perform equally or more accurately than other classification techniques. In a general way, the major advantages of the neural network method over traditional classifiers are: (1) easy adaptation to different types of data and input configuration; (2) easy incorporation of ancillary data sources, as textural information, which can be difficult or impossible with conventional techniques; (3) does not use unreasonable assumptions about statistics properties of the data, that is, does not need a priori knowledge about parameters of distributions; (4) finds the best nonlinear function, in the optimal case, between the input and the output data without any constraint of linearity or pre-specified nonlinearity which is required, for example, in regression analysis; (5) may be implemented with reduced storage and computation requirements.

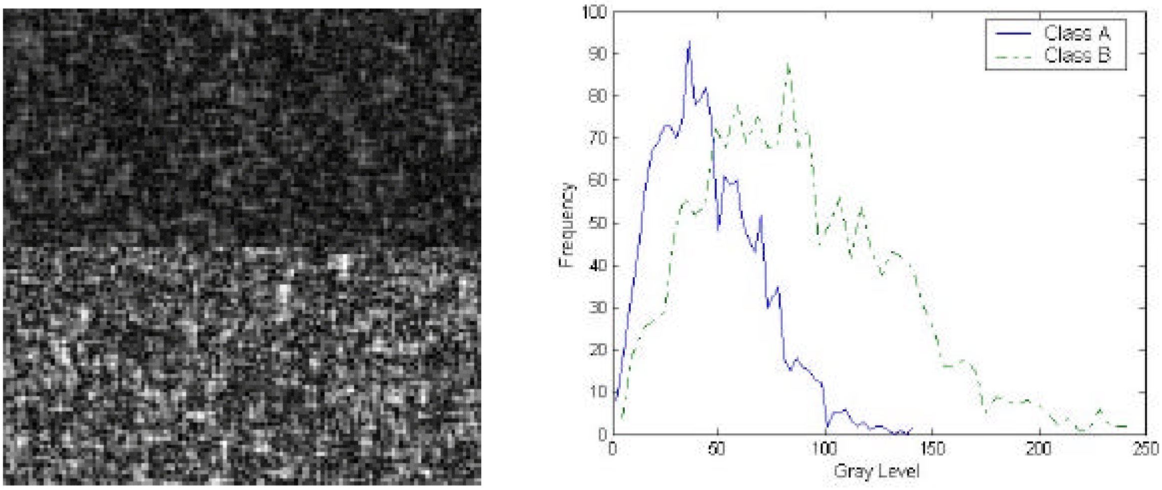
Hara et al. (1994) also showed that supervised neural network classifiers (NC) have outperformed unsupervised methods because the last one utilizes no a priori class information. Therefore, multi-layer feed-forward networks trained by the back-propagation algorithm is the most common ANN used for image processing due to its great classification potential and implementation simplicity.

Fully polarimetric SAR data were used to train a multi-layer feed-forward network using a dynamic Kalman filtering, as in Chen et al. (1996) and Tzeng and Chen (1998), while Ito and Omatu (1998) used the classical back-propagation. These data were also used to multitemporal data classification by Frate and Lichtenegger (1999) and Gedira et al. (2000). Texture information was explored by Ghinelli and Bennett (1997) and Jacob et al. (2002).

In this paper, it was investigated the classification performance for the supervised neural classifiers based on two different cost functions: the Minkovski-r error and the modified Fisher cost. The classification test was made via a multi-layer feed-forward artificial neural network, trained by using the back-propagation algorithm with the aim to extract filtering masks around a center pixel to be assigned to one of the two classes from a double textured SLC-SAR amplitude image with known edge. The performance was evaluated by using kappa statistics as function of the size of the masks and the number of samples used for learning. An analysis about the edge degradation was also investigated. The results were compared with two well-known statistical classifiers: the Minimum Bayes error and the Kullback-Liebler distance. Median filter was also used in the post-processing to increase the classification performance. In the next session, we describe the experimental data used for evaluating the classification performance. In section 3, the supervised neural network classifiers are described. Experimental results and conclusions are presented in section 4 and 5, respectively.

2. Experimental Data

To investigate the performance of the supervised neural classifiers, a spacial correlated Single Look Complex Synthetic Aperture Radar (SLC-SAR) images with two classes were simulated taking into account the multiplicative speckle noise. The image was generated by using a stationary circularly symmetric separable Gaussian Markov Random Field (GMRF), as in Fernandes (1998), with a correlation coefficient equals to 0.7 between the range and the azimuth pixels. This means the data employed in this work are realistic scenes.



(a) (b)

Figure 1. (a) 128x128 amplitude SAR image with two distinct classes and a known edge. (b) Histograms with 50x50 pixels per class region.

The aim here is to generate a simulated amplitude image with two distinct classes separated by *a priori* known edge. In this case, as in **Figure 1-(a)**, a resulting 128x128 pixels amplitude SAR image was created with two distinct classes Rayleigh distributed with expectance 45.00 for class A, the darker one, and 90.00 for class B. In **Figure 1-(b)**, a 50x50 pixels region from each class was put on a histogram that shows a large overlap between the distributions. The estimated values obtained were 45.09 and 579.58 for average and variance of the class A, respectively, and 87.24 and 2021.37 for the class B.

3. Supervised Neural Network Classifiers

The ANN architecture used to classify the double textured amplitude SAR image is a multi-layer feed-forward network that receives input from a (2M+1)x(2M+1), M>0, ordered and squared region around the pixel (r,c), or (row, column), to be classified. The input layer feeds through hidden layers to a single output node that assigns the center pixel (r,c) to one of the two classes, according to the output signal polarity. Conventionally, the weights from the input image to the first hidden layer neuron are called *mask* and the total output signal vector of this first hidden layer is called *feature vector*. The traditional hyperbolic tangent function was used in all the layers as the *activation function* due to its speed of convergence and low computational cost to implement the derivative.

The use of filtering masks based on regions classification as input images aims at reducing the dimensionality of the feature space and, therefore, at facilitating the ANN learning process due to reduction of the curse of dimensionality, as explained by Haykin (1999). The main idea here is if the ANN is successfully trained, the first hidden layer will extract optimal filters obtained by the masks, thereby enabling it to emphasize intrinsic characteristics in the classes of the image. Depending on data complexity, a subsequent hidden layer will be necessary and it will be able to help extracting other internal data representations. The single output neuron has the function to classify the center pixel (r,c).

Training the ANN means updating their synaptic weights in such a way that an objective function, or cost function, is maximized or minimized. The *Minkovski-r Error* (ME_r), or L_R norm, is a generalized metric distance where the r exponent is useful for various aspects of representing information, that is,

$$ME_r = \frac{1}{r}(y_d - y_o)^r,\ r > 0, \qquad \textbf{(1)}$$

where y_d is the output desired signal of the output neuron and y_o is its output signal measured. According to Bishop (1995), small r exponents, or $r < 2$, give less importance for large deviations in the error and tend to reduce the influence of *outlier* points in the feature space during learning. For the case $r = 2$, the cost function **(1)** reduces to the usual sum-of-squares error that boils down to the classical back-propagation deduction, as in Haykin (1999).

Traditionally, *Fisher criterion* is a tool to reduce the dimensionality of the input space of data to be classified by using its average and variance, as in Fukunaga (1990). The proposal here, according to Jacob et al. (2002), is to use the *modified Fisher Error* (FE) **(2)** instead of the complete one because it does not considerably affect the classification performance and is not so computationally expensive to train the network. So, we employ

$$FE = \frac{1}{2}(m_A - m_B)^2, \qquad \textbf{(2)}$$

where m_i, $i = A, B$, are the output signal neuron averaged by all the training data from class A and class B, respectively. In this case, in contrast to ME_r, the cost function must be maximized to a successful learning.

Here, to train the ANN we used a *steepest descent/ascent* algorithm implemented via back-propagation. Therefore, the cost functions **(1)** and **(2)** may not reach the global minimum/maximum and the filters extracted will not be optimal. To avoid this, genetic algorithm could be used, but this would increase the computational complexity considerably.

4. Experimental Results

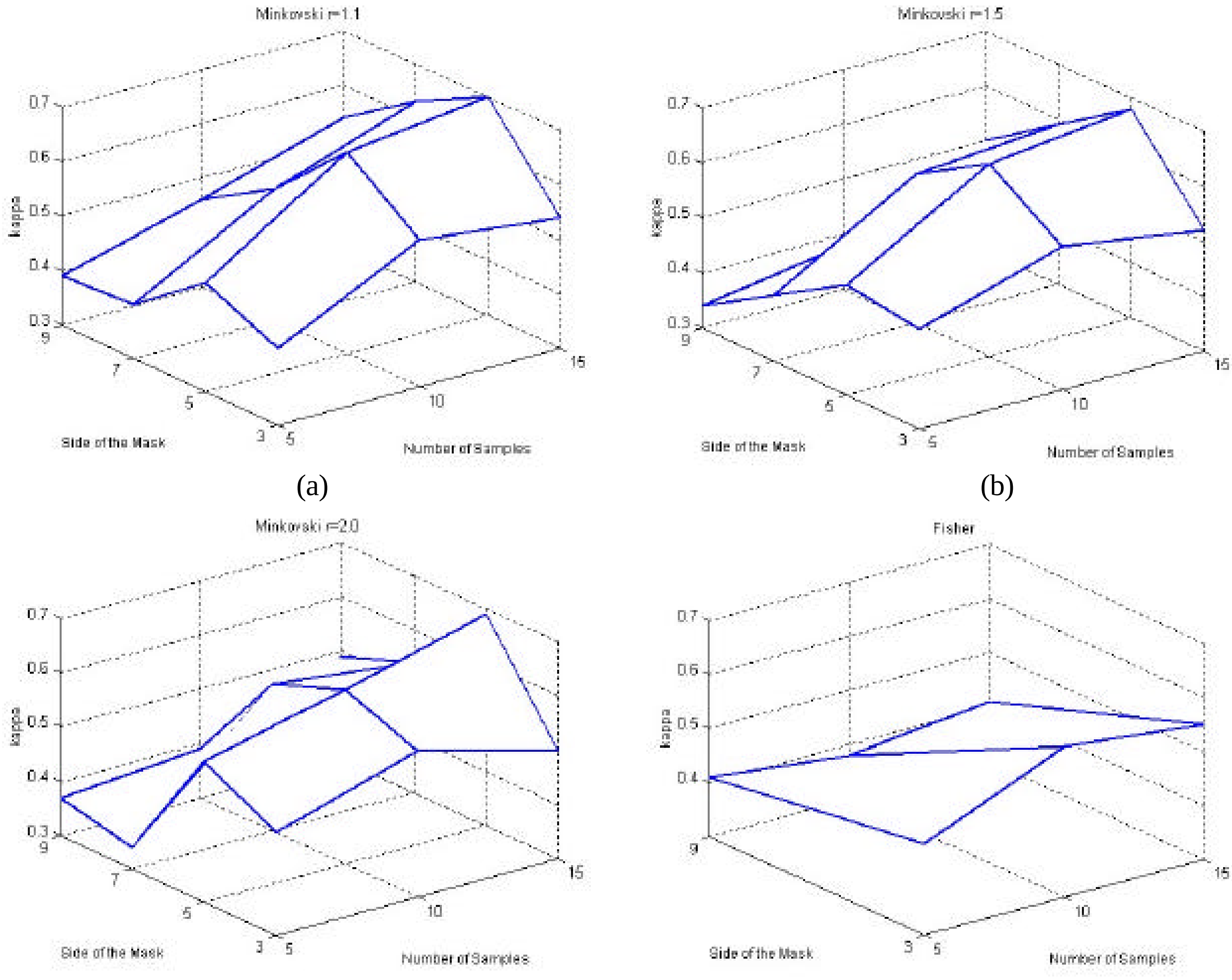
In this section, the performance results of four supervised neural classifiers (NC) used to classify the double textured amplitude SAR image from **Figure 1-(a)** are presented. The goal is to compare the performance for two different cost functions: the Minkovski-r Error and the modified Fisher cost, where in the first case three different exponents were used: r=1.1, r=1.5 and r=2.0. It was investigated the best classification performance based on kappa statistics, see Bishop et al. (1976), versus the size of the mask and the influence of the quantity of samples in the training.

In both cases, Minkovski and modified Fisher costs, the back-propagation was applied with a constant *learning rate parameter* and a speed-up *momentum term* until 1500 iterations were reached or when the *rate of change* is smaller than $5x10^{-4}$ for the first cost or 10^{-3} for the second one. For the Minkovski's cases, if the output signal is positive, the center pixel (r,c) is assigned to class A, and if is negative, to class B. But for the modified Fisher cost, the network performed a classification based on the matching of the output signal polarity and the *a priori* training data, because **(2)** has two possible solutions. Performance results based on kappa statistics are shown in **Figure 2**. *Kappa coefficient* was evaluated with more than 2500 points in each class. All data presented here has cost function smaller than 10^{-2} for the ME_r and larger than 1.8 for the FE, and the network topology has only one hidden layer with two neurons. Other more complex network topologies were tested but the classification performance improvement was only marginal.

Figure 2-(d) indicates that the network trained with the modified Fisher cost presented difficulty to learn with 5x5 and 7x7 mask sizes, so just two points were obtained. In a general way, all the cost variations, mainly in the Minkovski-r error, have almost the same performance. However, the Minkovski-r=1.1 showed a bit better results than the others. So, as discussed in **Section 3**, smaller r exponents decrease the effect of the outliers data training points. For all the Minkovski's classifiers, the best performance occurred with a 5x5 size mask and, except for r=2.0, the performance did not increase gradually as the number of data training were presented, that is, the over fitting occurred.

The performance results of the supervised neural classifiers were also compared with those obtained by two statistical classifiers: one based on the *Minimum Bayes error,* as in Fukunaga (1990), that generates a Bayes decision rule for the minimum misclassification error among classes; and other based on the *Kullback-Liebler distance* (K-L), as discussed in Carvalho (1999). For the both cases, it is assumed that the classes have *a priori* known distribution functions, so their respective parameters are extracted to solve the classification problem.

In **Table 1**, confusion matrices and their respective kappa coefficients were computed to represent the classification performance for the statistical classifiers. The best classification performance of the Minimum Bayes error method, that is, its optimal result, has shown a poor performance if compared to the K-L method. As showed in **Figure 1-(b)**, it occurs because there is a higher misclassification error between the classes A and B. For the K-L method, however, it was chosen 3 samples of 11x11 window per class to extract the parameters from the regions, and a 5x5 window performed the region attribution. In this last case, the minimum distance method showed better classification performance than the Minimum Bayes error and the supervised neural classifiers, as in **Table 2-(a)**. Slightly better results were obtained after a 3x3 Median filter (MF) decreases some speckled misclassifications.



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

Figure 2. Classification performance varying the size of the masks and the number of training samples using the following costs: (a) $ME_{1.1}$. (b) $ME_{1.5}$. (c) $ME_{2.0}$. (d) FE.

Table 1. Confusion matrices: Minimum Bayes error, simple K-L and K-L with Median filtering method for classes A and B.

Minimum Bayes Error			K-L			K-L + 3x3 MF		
Known Class	Classification		Known Class	Classification		Known Class	Classification	
	A	B		A	B		A	B
A	0.83	0.17	A	0.93	0.07	A	0.96	0.04
B	0.39	0.61	B	0.12	0.88	B	0.11	0.89
	Kappa = 0.44			Kappa = 0.80			Kappa = 0.84	

The supervised neural classified image, or supervised neural thematic map, also for the best results, has a higher number of misclassified points because the network had difficulty to learn the speckle noise. This occurred mainly in the class B, where the class variance is bigger than the class A. **Table 2** shows the confusion matrices and their respective kappa coefficients obtained by the supervised neural classifier (NC) trained with the Minkovski-r=1.1 cost, 5x5 window mask and 15 training samples per class. The simple NC obtained a fair classification. However, as presented in **Table 2-(b)** and **(c)**, increasingly better results were reached when using Median filters to erode the image.

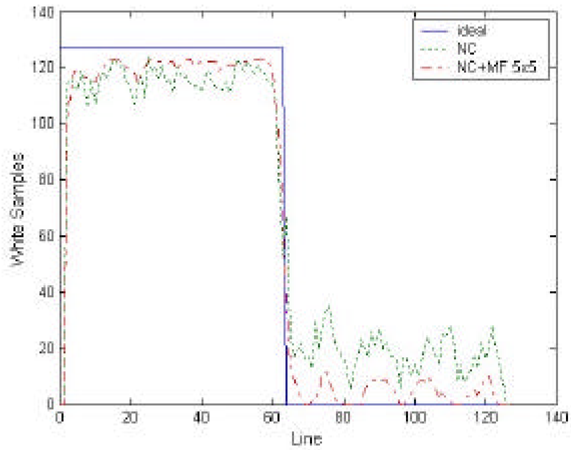
Table 2. Confusion matrices: 5x5 mask neural classifier based on $ME_{1.1}$ simple and with Median filtering for classes A and B.

Minkovski r=1.1		
Known Class	Classification A	Classification B
A	0.93	0.07
B	0.24	0.76
	Kappa = 0.69	

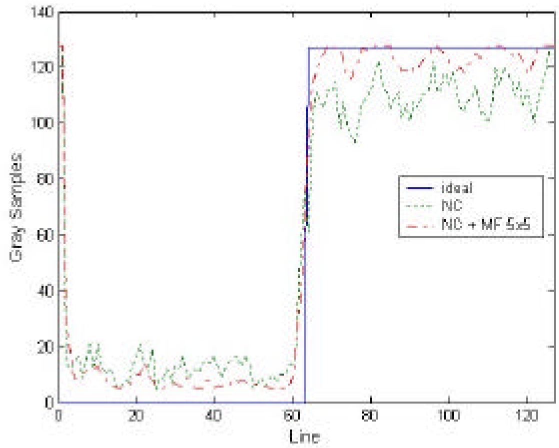
Minkovski r=1.1 + 3x3 MF		
Known Class	Classification A	Classification B
A	0.98	0.02
B	0.14	0.86
	Kappa = 0.84	

Minkovski r=1.1 + 5x5 MF		
Known Class	Classification A	Classification B
A	0.99	0.01
B	0.08	0.92
	Kappa = 0.91	

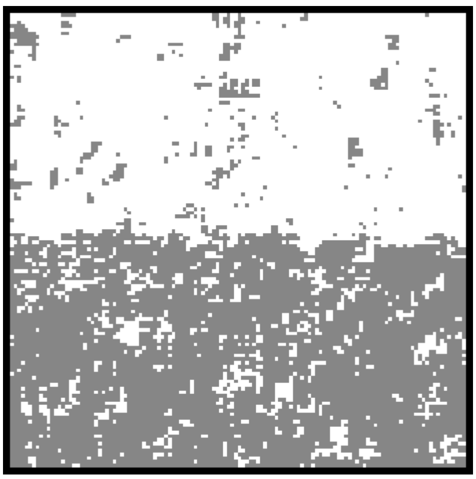
Figure 3-(a) and **(b)** show histograms that contain the number of points classified in each image line as class A and class B the neural classified thematic map obtained by the 5x5 mask Minkovski-r=1.1's NC trained with 15 samples per class. These graphics are able to show the edge degradation and the classification performance in a qualitative way. Then, with a 5x5 size mask, the edge degradation is about 3 or 4 pixels around the ideal known edge and the 5x5 size mask Median filter, when passed through the edge, makes the region a bit more uniform. **Figure 3-(c)** and **(d)** present the result images without and with the Median filtering, where the black pixels represent the edge effect occurred by the filtering masks.



(a)



(b)


(c)

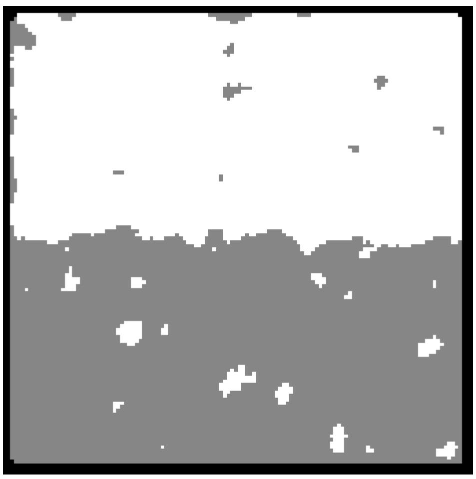

(d)

Figure 3. (a) Number of points classified as white samples or class A by image line. (b) Number of points classified as gray samples or class B by image line. (c) Neural classified thematic map for the 5x5 size mask trained via Minkovski-r=1.1 and 15 samples per class. (d) Last image eroded by a 5x5 Median filter.

The investigation showed that the minimum Bayes error is not a good method to classify images with an elevated misclassification error due to the Rayleigh distribution classes. The K-L method has better results, however needs a higher amount of training information to extract the well-known parameters of the distribution classes. In our case, for example, the image does not have any additive thermal noise or other that represents any other undesired information. For NC, in contrast, it does not matter if there are noise or not, because it does not assume any parametric well-known distribution.

5. Conclusions

In this paper, four supervised neural network classifiers were applied to a simulated SAR image with just two classes. The main goal was to carry out to a detailed performance evaluation on the same data set, in contrast to the available literature, which usually deals with a single application, thereby rising the question if a better result could be obtained otherwise. Additionally, the performance of the neural network classifiers, when compared with statistical classifiers, was better than the minimum Bayes error and slightly better than the K-L method, when a Median filter is used in the post-processing.

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Referências

Benediktsson, J. A.; Swain, P. H.; Ersoy, O. K. Neural Network approaches versus statistical methods in classification of multisource remote sensing data. *IEEE Trans. Geosci. Remote Sensing*, v. 28, n. 4, p. 540-552, 1990.

Bischof, H.; Schneider, W.; Pinz, A. J. Multispectral classification of landsat-images using neural networks. *IEEE Trans. Geosci. Remote Sensing*, v. 30, n. 3, p. 482-490, 1992.

Bishop, C. M. *Neural networks for pattern recognition*. Oxford: Claredon Press, 1995.

Bishop, Y. M. M.; Fienberg, S. E.; Holland, P. W. *Discrete multivariate analysis: theory and practice*. Cambridge: MIT Press, 1976.

Carvalho, L. S. G. *Classificação supervisionada de imagens SAR*. Trabalho de Graduação – ITA, São José dos Campos, 1999.

Chen, K. S.; Huang, W. P.; Tsay, T. H.; Amar, F. Classification of multifrequency polarimetric SAR imagery using a dynamic learning neural network. *IEEE Trans. Geosci. Remote Sensing*, v. 34, n. 3, p. 814-820, 1996.

Frate, F. D.; Lichtenegger, J. Monitoring urban areas by using ERS-SAR data and neural network algorithms. In: International Geoscience and Remote Sensing Symposium, Hamburgo, jul. 1999. *Anais*.

Fernandes, D. Simulation of speckled SAR interferogram. In: European Conference on Synthetic Aperture Radar, Friedrichshafen, 1998. *Anais*.

Fukunaga, K. *Introduction to Statistical Pattern Recognition*. Segunda Edição. San Diego: Academic Press, 1990.

Ghedira, H.; Bernier, M.; Ouarda, T. B. M. J. Application of neural networks for wetland classification in RADARSAT SAR imagery. In: International Geoscience and Remote Sensing Symposium, Honolulu, jul. 2000. *Anais*.

Ghinelli, B. M. G.; Bennett, J. C. The application of artificial neural networks to radar image classification. In: International Geoscience and Remote Sensing Symposium, Singapura, ago. 1997. *Anais*.

Hara, Y.; Atkins, R. G.; Yueh, S. H.; Shin, R. T.; Kong, J. A. Application of neural networks to radar image classification. *IEEE Trans. Geosci. Remote Sensing*, v. 32, n. 1, p. 100-109, 1994.

Haykin, S. *Neural networks: a comprehensive foundation*. Upper Saddle River: Prentice Hall, 1999.

Ito, Y.; Omatu, S. A Polarimetric SAR data classification method using neural networks. In: International Geoscience and Remote Sensing Symposium, Seattle, jul. 1998. *Anais*.

Jacob, A. M.; Hemerly, E. M.; Fernandes, D. SAR image classification using a neural classifier based on Fisher criterion. In: Simpósio Brasileiro de Redes Neurais, Porto de Galinhas, nov. 2002. *Anais*.

Oliver, C.; Quegan, S. *Understanding synthetic aperture radar images*. Norwood: Artech House, 1998.

Tzeng, Y. C.; Chen, K. S. A fuzzy neural network to SAR image classification. *IEEE Trans. Geosci. Remote Sensing*, v. 36, n. 1, p. 301-307, 1998.