Expert Systems with Applications 39 (2012) 4710–4717

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Evolutionary RBF classifier for polarimetric SAR images

Turker Ince [a,*], Serkan Kiranyaz [b], Moncef Gabbouj [b]

[a] Izmir University of Economics, Electronics and Telecommunications Engineering Department, Izmir, Turkey
[b] Tampere University of Technology, Department of Signal Processing, Tampere, Finland

ARTICLE INFO

Keywords:
Polarimetric synthetic aperture radar
Radial basis function network
Particle swarm optimization

ABSTRACT

In this paper, a robust radial basis function (RBF) network based classifier is proposed for polarimetric synthetic aperture radar (SAR) images. The proposed feature extraction process utilizes the covariance matrix elements, the H/α/A decomposition based features combined with the backscattering power (span), and the gray level co-occurrence matrix (GLCM) based texture features, which are projected onto a lower dimensional feature space using principal components analysis. For the classifier training, both conventional backpropagation (BP) and multidimensional particle swarm optimization (MD-PSO) based dynamic clustering are explored. By combining complete polarimetric covariance matrix and eigenvalue decomposition based pixel values with textural information (contrast, correlation, energy, and homogeneity) in the feature set, and employing automated evolutionary RBF classifier for the pattern recognition unit, the overall classification performance is shown to be significantly improved. An experimental study is performed using the fully polarimetric San Francisco Bay and Flevoland data sets acquired by the NASA/Jet Propulsion Laboratory Airborne SAR (AIRSAR) at L-band to evaluate the performance of the proposed classifier. Classification results (in terms of confusion matrix, overall accuracy and classification map) compared with the major state of the art algorithms demonstrate the effectiveness of the proposed RBF network classifier.

1. Introduction

Image and data classification techniques play an important role in the automatic analysis and interpretation of remote sensing data. Particularly polarimetric synthetic aperture radar (SAR) data poses a challenging problem in this field due to complexity of measured information from its multiple polarimetric channels. Recently, the number of applications which use data provided by the SAR systems having fully polarimetric capability have been increasing. Over the past decade, there has been extensive research in the area of the segmentation and classification of polarimetric SAR data. In the literature, the classification algorithms for polarimetric SAR can be divided into three main classes: (1) classification based on physical scattering mechanisms inherent in data (Pottier & Lee, 2000; van Zyl, 1989), (2) classification based on statistical characteristics of data (Lee et al., 1999; Wu, Ji, Yu, & Su, 2008) and (3) classification based on image processing techniques (Ince, 2010; Tan, Lim, & Ewe, 2007; Ye & Lu, 2002). Additionally, there has been several works using some combinations of the above classification approaches (Lee et al., 1999; Pottier & Lee, 2000). While these approaches to the polarimetric SAR classification problem can be based on either supervised or unsupervised methods, their performance and suitability usually depend on applications and the availability of ground truth.

As one of the earlier algorithms, Kong, Swartz, Yueh, Novak, and Shin (1988) derived a distance measure based on the complex Gaussian distribution and used it for maximum-likelihood (ML) classification of single-look complex polarimetric SAR data. Then, Lee, Grunes, and Kwok (1994) used the statistical properties of a fully polarimetric SAR to perform a supervised classification based on complex Wishart distribution. Afterwards, Cloude and Pottier (1997) proposed an unsupervised classification algorithm based on their target decomposition theory. Target entropy (H) and target average scattering mechanism (scattering angle, α) calculated from this decomposition have been widely used in polarimetric SAR classification. For multilook data represented in covariance or coherency matrices, Lee et al. (1999) proposed a new unsupervised classification method based on combination of polarimetric target decomposition (Cloude & Pottier, 1997) and the maximum likelihood classifier using the complex Wishart distribution. The unsupervised Wishart classifier has an iterative procedure based on the well-known *K-means* algorithm, and has become a preferred benchmark algorithm due to its computational efficiency and generally good performance. However, this classifier still has some significant drawbacks since it entirely relies on *K-means* for actual clustering, such as it may converge to local optima, the number of clusters should be fixed *a priori*, its performance is sensitive to the

* Corresponding author. Tel.: +90 2324888509; fax: +90 2324888475.
E-mail address: turker.ince@ieu.edu.tr (T. Ince).

0957-4174/$ - see front matter
doi:10.1016/j.eswa.2011.09.082

initialization and its convergence depends on several parameters. Recently, a two-stage unsupervised clustering based on the EM algorithm (Khan, Yang, & Zhang, 2007) is presented for classification of polarimetric SAR images. The EM algorithm estimates parameters of the probability distribution functions which represent the elements of a 9-dimensional feature vector, consisting of six magnitudes and three angles of a coherency matrix. Markov random field (MRF) clustering based method (Tran, Wehrens, Hoekman, & Buydens, 2005) exploiting the spatial relation between adjacent pixels in polarimetric SAR images has been presented. In (Ye & Lu, 2002), a new wavelet-based texture image segmentation algorithm is successfully applied to unsupervised SAR image segmentation problem.

More recently, neural network based approaches (Yang, Wang, & Jiao, 2009; Zhang, Wu, & Wei, 2009; Zhang, Zou, Zhang, & Zhang, 2010) for classification of polarimetric synthetic aperture radar data have been shown to outperform other aforementioned well-known techniques. Compared with other approaches, neural network classifiers have the advantage of adaptability to the data without making *a priori* assumption of a particular probability model or distribution. However, their performance depends on the network structure, training data, initialization, and parameters. Designing an optimal ANN classifier structure and its parameters to maximize the classification accuracy is still a crucial and challenging task. In this study, RBF network classifier which is optimally designed by the evolutionary search technique, multidimensional particle swarm optimization (MD-PSO) (Kiranyaz, Ince, Yildirim, & Gabbouj, 2010), is employed. RBFs are chosen due to their robustness, faster learning capability compared with other feedforward networks, and superior performance with simpler network architectures. Earlier work on RBF classifiers for polarimetric SAR image classification has demonstrated a potential for performance improvement over conventional techniques (Ince, 2010). The proposed polarimetric SAR feature vector includes full covariance matrix, the H/α/A decomposition based features combined with the backscattering power (*Span*), and the gray level co-occurrence matrix (GLCM) based texture features as suggested by the results of previous studies (Clausi & Yue, 2004; Ersahin, Scheuchl, & Cumming, 2004). The performance of the proposed RBF network based classifier is evaluated using the fully polarimetric San Francisco Bay and Flevoland data sets acquired by the NASA/Jet Propulsion Laboratory Airborne SAR (AIRSAR) at L-band. The classification results (in terms of confusion matrix, overall accuracy and classification map) are compared with competing state of the art classifiers.

The rest of the paper is organized as follows. Section 2 briefly presents the basic theory of polarimetric SAR for this paper including the Cloude–Pottier decomposition. The feature extraction methodology for the proposed polarimetric SAR image classification system is described in Section 3. Then, the RBF network fundamentals, its training algorithms, and an overview of the proposed classifier technique are presented in Section 4. Section 5 describes the experimental test results on real polarimetric SAR data. Finally, Section 6 concludes the paper.

2. Polarimetric sar data processing

Polarimetric radars often measure the complex scattering matrix, $[S]$, produced by a target under study with the objective to infer its physical properties. Assuming linear horizontal and vertical polarizations for transmitting and receiving, $[S]$ can be expressed as

$$S = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} \tag{1}$$

Reciprocity theorem applies in a monostatic system configuration, $S_{hv} = S_{vh}$. For coherent scatterers only, the decompositions of the measured scattering matrix $[S]$ can be employed to characterize the scattering mechanisms of such targets. One way to analyze coherent targets is the Pauli decomposition (Lee et al., 1999), which expresses $[S]$ in the so-called Pauli basis $\left\{[S]_a = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix},\right.$ $[S]_b = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix},\ [S]_c = \frac{1}{\sqrt{2}}\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}\Big\}$ as,

$$S = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} = \alpha[S]_a + \beta[S]_b + \gamma[S]_c \tag{2}$$

where $\alpha = (S_{hh} + S_{vv})/\sqrt{2}, \beta = (S_{hh} - S_{vv})/\sqrt{2}, \gamma = \sqrt{2}S_{hv}$. Hence, by means of the Pauli decomposition, all polarimetric information in $[S]$ could be represented in a single RGB image by combining the intensities $|\alpha|^2$, $|\beta|^2$ and $|\gamma|^2$, which determine the power scattered by different types of scatterers such as single- or odd-bounce scattering, double- or even-bounce scattering, and orthogonal polarization returns by the volume scattering. There are several other coherent decomposition theorems such as the Krogager decomposition, the Cameron decomposition, and SDH (Sphere, Diplane, Helix) decomposition all of which aim to express the measured scattering matrix by the radar as the combination of scattering responses of coherent scatterers.

Alternatively, the second order polarimetric descriptors of the average polarimetric covariance $\langle[C]\rangle$ and the coherency $\langle[T]\rangle$ matrices can be derived from the scattering matrix and employed to extract physical information from the observed scattering process. The elements of the covariance matrix, $[C]$, can be written in terms of three unique polarimetric components of complex scattering matrix:

$$\begin{aligned} C_{11} &= S_{hh}S_{hh}^*, \quad C_{21} = S_{hh}^*S_{hv} \\ C_{22} &= S_{hv}S_{hv}^*, \quad C_{32} = S_{hh}^*S_{vv} \\ C_{33} &= S_{vv}S_{vv}^*, \quad C_{11} = S_{hh}^*S_{vv} \end{aligned} \tag{3}$$

For single-look processed polarimetric SAR data, the three polarimetric components (*HH*, *HV*, and *VV*) has a multivariate complex Gaussian distribution and the complex covariance matrix form has a complex Wishart distribution (Lee et al., 1994). Due to presence of speckle noise and random vector scattering from surface or volume, polarimetric SAR data are often multi-look processed by averaging n neighboring pixels. By using the Pauli based scattering matrix for a pixel i, $k_i = [S_{hh} + S_{vv}, S_{hh} - S_{vv}, 2S_{hv}]^T/\sqrt{2}$, the multi-look coherency matrix, $\langle[T]\rangle$, can be written as

$$\langle T\rangle = \frac{1}{n}\sum_{i=1}^{n} k_i k_i^{*T} \tag{4}$$

Both coherency $\langle[T]\rangle$ and covariance $\langle[C]\rangle$ are 3×3 Hermitian positive semidefinite matrices, and since they can be converted into one another by a linear transform, both are equivalent representations of the target polarimetric information.

The incoherent target decomposition theorems such as the Freeman decomposition, the Huynen decomposition, and the Cloude–Pottier (or H/α/A) decomposition employ the second order polarimetric representations of PolSAR data (such as covariance matrix or coherency matrix) to characterize distributed scatterers. The H/α/A decomposition (Cloude & Pottier, 1996) is based on eigen analysis of the polarimetric coherency matrix, $\langle[T]\rangle$:

$$\langle T\rangle = \lambda_1 e_1 e_1^{*T} + \lambda_2 e_2 e_2^{*T} + \lambda_3 e_3 e_3^{*T} \tag{5}$$

where $\lambda_1 > \lambda_2 > \lambda_3 \geqslant 0$ are real eigenvalues and the corresponding orthonormal eigenvectors e_i (representing three scattering mechanisms) are

$$e_i = e^{i\phi_i}[\cos\alpha_i, \sin\alpha_i\cos\beta_i e^{i\delta_i}, \sin\alpha_i\sin\beta_i e^{i\gamma_i}]^T \tag{6}$$