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Comparison of Various Classification Algorithms for Polarimetric SAR Image Classification

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***Abstract*: In this paper, variety of classifiers for supervised target classification of polarimetric synthetic aperture radar (SAR) image explained. Compared to traditional classifiers such as ML classification,complex Wishart distribution or Adabo0st classifier, the SVM (Support Vector Machine) method is more robust, accurate and flexible. This algorithm not only uses a statistical classifier, but also preserves the purity of dominant polarimetric scattering properties. Different features or parameters extracted from Polarimetric SAR data could be adopted into the scheme and a quantitative analysis on the significance of each parameter for classification could be achieved. Experiment results demonstrated the effectiveness of the SVM.**

Keywords: synthetic aperture radar (SAR), Polarimetry, supervised classification, support vector machine (SVM)

1. INTRODUCTION

Terrain and land-use classification are arguably the most important applications of polarimetric synthetic aperture radar (SAR). Many supervised and unsupervised classification methods have been proposed [1]–[14]. Earlier classification algorithms classify polarimetric SAR images based on their statistical characteristics [1]–[8]. For single-look complex polarimetric SAR data, Kong *et al.* [4] derived a distance measure for maximum-likelihood classification based on the complex Gaussian distribution [15]. Yueh *et al.* [5] and Lim *et al.* [6] extended it for normalized polarimetric SAR data. van Zyl and Burnette [7] further expanded this approach by iteratively applying the *a priori* probabilities of the classes. For multilook data represented in covariance or coherency matrices, Lee *et al.* [8] derived a distance measure based on the complex Wishart distribution [15]. This distance measure has been incorporated in developing other POLSAR classification algorithms [11]–[14]. Ferro-Famil *et al.* [13], [14] have extended this class of classification algorithms to multifrequency, and to polarimetric SAR interferometry data, using interferometric coherences to separate man-made targets from vegetated areas. An alternative approach is to classify polarimetric SAR images based on the inherent characteristics of physical scattering mechanisms. This approach has the additional advantage of providing information for class type identification. van Zyl [9] proposed to classify terrain types as odd bounce, even bounce, and diffuse scattering. For a refined classification into more classes, Cloude and Pottier [10] proposed an unsupervised classification algorithm based on their target decomposition theory. Scattering mechanisms, characterized by entropy H and angle, are used for classification. The H plane is divided into eight zones and eight classes. The physical scattering characteristics associated with each zone provide information for terrain type assignment. The deficiency of this approach is that the classification result lacks details, because of the preset zone boundaries in the H and plane. Clusters may fall on the boundaries, and more than one cluster may be enclosed in a zone. A combined use of physical scattering characteristics and statistical properties for terrain classification is desirable. Such an algorithm has been proposed by Lee *et al.* [11], which applied the Cloude and Pottier decomposition scheme for initial classification, followed by iterated refinement using the complex Wishart classifier. Significant improvement in classification of details during iterations was observed. Pottier and Lee [12] further improved this algorithm by including anisotropy to double the number of classes to 16. In both algorithms, the final classification can be substantially different from initial classified results, and pixels of different scattering mechanisms could be mixed together, because the Wishart iteration is based only on the statistical characteristics of each pixel. Thus, the physical scattering characteristics are ignored for pixel reassignment during iterations.

The aim of this paper is two fold: First, it is to assess the potential of radar polarimetric data for land use classification over a tropical environment. Second, it is to evaluate the contribution of different polarimetric indicators for such application. To this end, a support vector machine (SVM) classification method is used since it is well suited to handle linearly nonseparable cases by using the Kernel theory [14]. Among other advantages, this method allows defining feature vectors with numerous and heterogeneous components. It has been mostly applied to hyper spectral remotely sensed data, and a few studies have also been carried out on SAR data [15], [16].

In the next all sections we will introduce Polarimetric data & parameters & basic five types of classification techniques used now a day for various applications and then the last section introduces the comparison statistics which helps to decide which classification methodology will be preferred.

2. POLARIMETRIC DATA & PARAMETERS

Polarimetric radar measures the complex scattering matrix of a medium with quad polarizations. We can simply divide the polarimetric features into two categories: one is the features based on the original data and its simple transform, and the other is based on target decomposition theorems. The first category features in this work mainly include the Sinclair scattering matrix, the covariance matrix, the coherence matrix, and several polarimetric parameters. The classical 2 × 2 Sinclair scattering matrix *S* can be achieved through the construction of system vectors

$$S = \begin{pmatrix} S_{HH} S_{HV} \\ S_{VH} S_{VV} \end{pmatrix}$$

In the monostatic backscattering case, for a reciprocal target matrix, the reciprocity constrains the Sinclair scattering matrix to be symmetrical, that is, $S_{HV} = S_{VH}$. Thus, the two target vectors *kp* and Ω_l can be constructed based on the Pauli and lexicographic basis sets, respectively. With the two vectorizations we can then generate a coherency matrix *T* and a covariance matrix *C* as follows:

$$K_p = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{HH} + S_{VV} \\ S_{HH} - S_{VV} \\ 2S_{HV} \end{bmatrix} \qquad ; [T] = \left\langle K_p . K_P{}^{*T} \right\rangle$$

$$\Omega_l = \begin{bmatrix} S_{HH} \\ \sqrt{2} S_{HV} \\ S_{VV} \end{bmatrix} \quad ; \quad [C] = \left\langle \Omega_l . \Omega_l{}^{*T} \right\rangle$$

All the classifiers accepts these features as an input for classification and depending upon the optimum feature selection for a particular application,any one classifier can be adopted for successful classification of Polarimetric SAR Image.

3. POLARIMETRIC SAR CLASSIFICATION ALGORITHM

(a) Maximum Likelihood Classifier: Maximum Likelihood (ML) technique is one of the most popular methods for SAR image classification. It determines the distributions of the information extracted from the image in each band for each class. Each unknown pixel is then assigned to a class based upon Gaussian probability. The likelihood function is given as follows on the assumption that the ground truth data of class *k* will form the Gaussian distribution [25].

$$L_i(X) = \frac{1}{(2\Pi)^{\Pi/2} |S_i|^{1/2}} \exp\left[-\frac{1}{2} (X - \overleftarrow{X})^T S_i{}^{-1} (X - X_i) \right]$$

Where $$X = \begin{bmatrix} X1 \\ X2 \\ X3 \\ . \\ . \\ Xn \end{bmatrix}$$

Xi is the mean vector of the ground truth data in class *i, Si* is the variance-covariance matrix of *i* class produced from the ground truth data and *Si* is the determinant of *Si* . The ML classifier is popular because of its robustness and simplicity. It also provides a consistent approach to parameter estimation problems. In addition, ML classifier has desirable mathematical and optimality properties. From the statistical point of view, with the small value of variance, a narrow confidence interval can be obtained, resulting an accurate classification of the image [26].

(b) Adaboost Classifier: Boosting is a powerful and well-studied method of finding a highly accurate classifier by combining many weak classifiers generated by a base learning algorithm. The final hypothesis is, typically, a weighted vote of the weak hypotheses. By keeping each of the weak hypotheses to be a simple rule, one can then control the complexity of the final hypothesis, and thereby, using VC-theory [10], expect a low error on the test examples as well. A major breakthrough came in the form of Freund and Schapire’s ADABOOST algorithm [11] which is extremely efficient and also very easy to implement. It has received extensive empirical and theoretical study and has been found to work very well on several practical two-class classification problems. Throughout this work we apply the variant of the AdaBoost algorithm presented by Viola and Jones [12]. This variant restricts the weak classifiers to depend on single-valued features fj only. The algorithm is described as follows: The AdaBoost procedure can be easily interpreted as a greedy feature selection process. Consider the general problem of boosting, in which a large set of classification functions are combined using a weighted majority vote. The challenge is to associate a large weight with each good classification function and a smaller weight with poor functions. AdaBoost is an aggressive mechanism for selecting a small set of good classification functions which nevertheless have significant variety. Drawing an analogy between weak classifiers and features, AdaBoost is an effective procedure for searching out a small number of good ”features” which nevertheless have Significant variety.

(c) Freeman Decomposition: In 1998, Freeman [4]proposed a polarimetric target decomposition algorithm based on a three-component scattering model. Assuming that the reciprocity of scattering came into existence, Freeman designed the modeling of three important scattering mechanisms--- volume (or canopy) scattering, double-bounce scattering and surface scattering. For volume scattering, it is assumed that the radar return is from a cloud of randomly oriented, very thin, and cylinder-like scatterers. Double-bounce scattering is modeled by scattering from a dihedral corner reflector, where the reflector surfaces can be made of different dielectric materials. Finally, surface scattering is modeled by a first-order Bragg modeling. By making several simplifying assumptions, the second-order statistics of the resulting three covariance matrixes can be derived. Based on these models, Freeman thought that the covariance matrix of target can be represented by the weighted sum of the covariance matrices of three scattering mechanisms:

$$<[C]>=f_v[C_V]+f_s[C_S]+f_D[C_D]$$

Further according to the conclusion of van Zyl [5], the decomposition coefficients of the three scattering mechanisms can be obtained by Freeman
decomposition, and the dominant scattering mechanism of target can be determined by comparing three coefficients.

(d) Wishart Distribution Classifiers: Assuming that the reciprocity principle is satisfied, the complex scattering vector measured by a fully polarimetric SAR is $x = [S_{HH} \quad \sqrt{2}S_{HV} \quad S_{VV}]^T$ where “T” denotes the matrix transpose.For dual-polarization SAR, the scattering vector is :

x=[S_1 S_2]^T where the subscripts "1" and "2" denote HH,HV or VV.The polarimetric covariance matrix is [1] as follows:

$$C = \left(\sum_{i=1}^{L} x_i x_i^{\ H} \right) / L$$

Where L is the number of looks,xi is the ith look sample of x and "H" refers to the complex conjugate transpose. C has the complex Wishart distribution[11].

$$p^{(L)}(C) = \frac{L^{qL} |C|^{L-q} \exp\{-LT_r(\sum^{-1} C)\}}{R(L,q) \left|\sum^{L}\right|}$$

Where ∑=E{C}is the ensemble average of C, q is the number of polarimetric channels.Tr(.) and {.} denote the trace and determinant of a matrix, respectively .R(L,p)=$\pi^{q(q-1)/2}$ £(L).....£(L-q+1) is the normalization factor, and £(.) is the gamma function.

(e) Support Vector Machine: Support vector machine theory is based on statistical learning theory and the minimization principle to structure risk. It has stronger generalization ability. The basic principle of the SVM is to find the optimal linear hyperplane such that the expected classification error for unseen test samples is minimized. On the basis of this principle, a linear SVM uses a systematic approach to find a linear function with the lowest VC dimension. For nonlinear separable data, the SVM can map the input to a high dimensional feature space where a linear hyperplane can be found. Therefore a good generalization can be achieved by the SVM compared to conventional classifiers [2]. In the case of a linear separable two-class problem, with examples {(x_1, y_1), (x_2, y_2)...... (x_m, y_m)}, the final optimal decision function can be obtained:

$$f(x) = \text{sgn}\left\{ \sum_{i=1}^{m} \alpha_i y_i (x_i . x) + b \right\} \qquad (1)$$

For a linear SVM, the kernel function is just a simple dot product in the input space. For a nonlinear SVM, the samples can be projected to a feature space of higher dimension via a nonlinear mapping function. Then the optimal decision function can be written as:

$$f(x) = \text{sgn}\left\{ \sum_{i=1}^{m} \alpha_i y_i (x_i , x) + b \right\} \qquad (2)$$

Where K(x, xi) is the kernel function. The kernel function in the SVM classifier plays the important role of implicitly mapping the input vector into a high dimensional feature space. There is currently no technique available to learn the form of kernels. Common choices of kernel function are the linear kernels, polynomial kernels, and Gaussian RBF kernels in SVM research. They are defined as follows:

- Linear kernels

$$k(x, x_i) = x.x_i \qquad (3)$$

- Polynomial kernels

$$k(x, y) = [(x.x_i) + 1]^q \qquad (4)$$

- Guassian RBF kernels

$$k(x, y) = \exp\left\{ -\frac{|x - x_i|^2}{\sigma^2} \right\} \qquad (5)$$

4. EXPERIMENTAL RESULTS

Examples are given in this section to illustrate the effectiveness of this classification algorithm. NASA/JPL AIRSAR L-band data of San Francisco are used to show the applicability of this algorithm for general terrain classification using the original four-look data. The spatial resolution is about 10 *10 m. This polarimetric SAR data has 700*901 pixels. The radar incidence angles span from 5 to 60 . This data was originally four-look processed. To retain the resolution, no speckle filtering or additional averaging is applied. This scene contains scatterers with a variety of distinctive scattering mechanisms. The original POLSAR image is displayed in Fig. 1(a), with Pauli matrix components: HH VV HV , and HH VV , for the three composite colors: red, green, and blue, respectively. The Maximum Likelihood Classification is shown in Fig.2(b). The Freeman decomposition using , and for red, green, and blue is shown in Fig. 2(c). The Freeman decomposition possesses similar characteristics to the Pauli-based decomposition, but Freeman decomposition provides a more realistic representation, because it uses scattering models with dielectric surfaces. In addition, details are sharper. The Classification results by Adaboost Classifier are clearly shown in Fig 2(d).The most accurate classification is achieved by recent classifier SVM is shown in Fig.2(e).Comparison of classification accuracy in NASA/JPL AIRSAR L-band data of San Francisco is explained in Table 1.

5. CONCLUSION

We addressed the problem of classifying POLSAR image with help of different classifiers. Firstly,using PolSARpro4.2 software we present an evolution of different features for POLSAR image classification with classifiesr. And the operation of all classifiers are proposed. After evolution, the features are concatenated & optimum feature selection for SVM is performed on the combined feature. Our observation suggests can get the feature weight as well as the SVM parameters. According to the feature weights vector, those features with non-zero weights are selected out and subsequently used for classification. SVM actually improves the classification rate, computation efficiency and complex by effectively pruning away irrelevant features.

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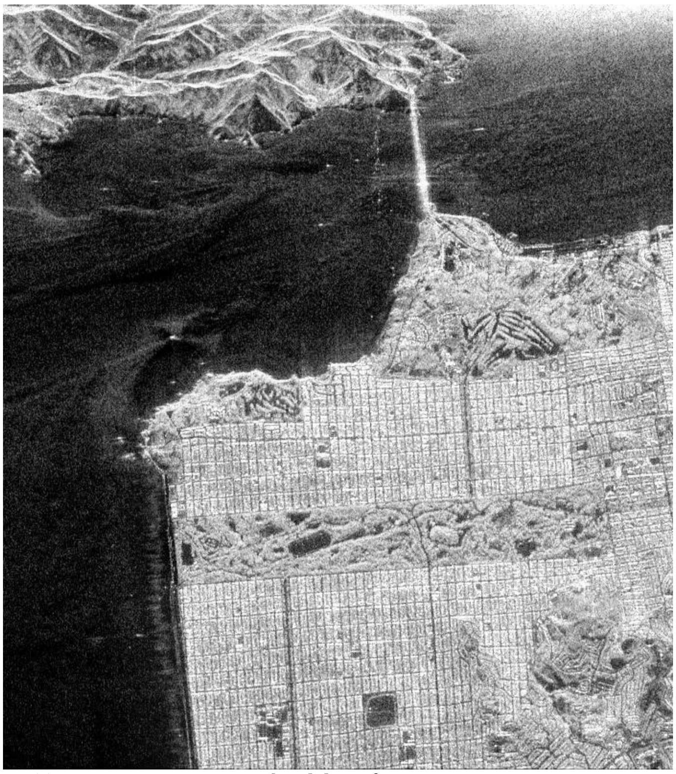
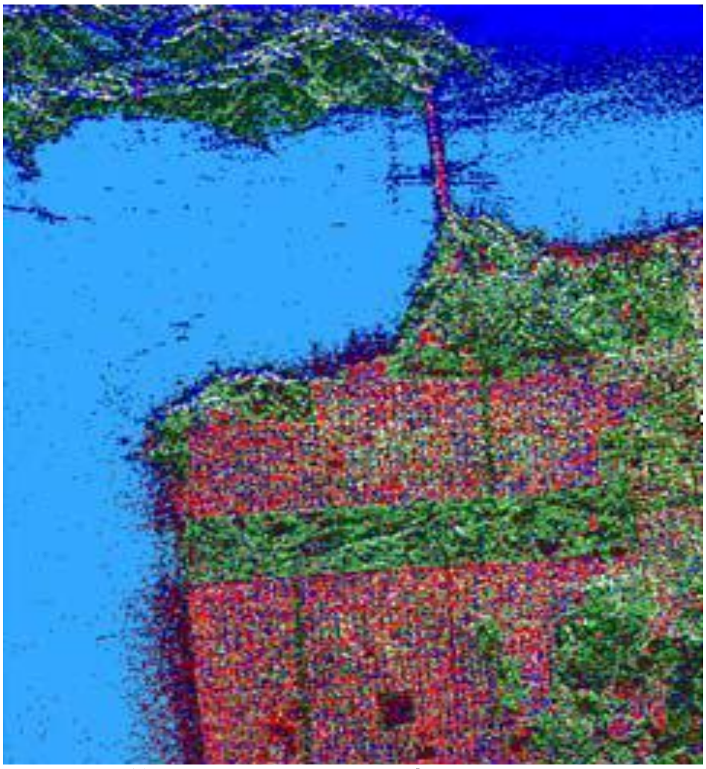
Table 1. Performance Comparison of different classifiers

Name of the Classifier	Overall Training Time (s)
ML	154.28
Freeman Decomposition	65.56
Adaboost	41.76
Wishart Distribution	40.66
SVM	34.87

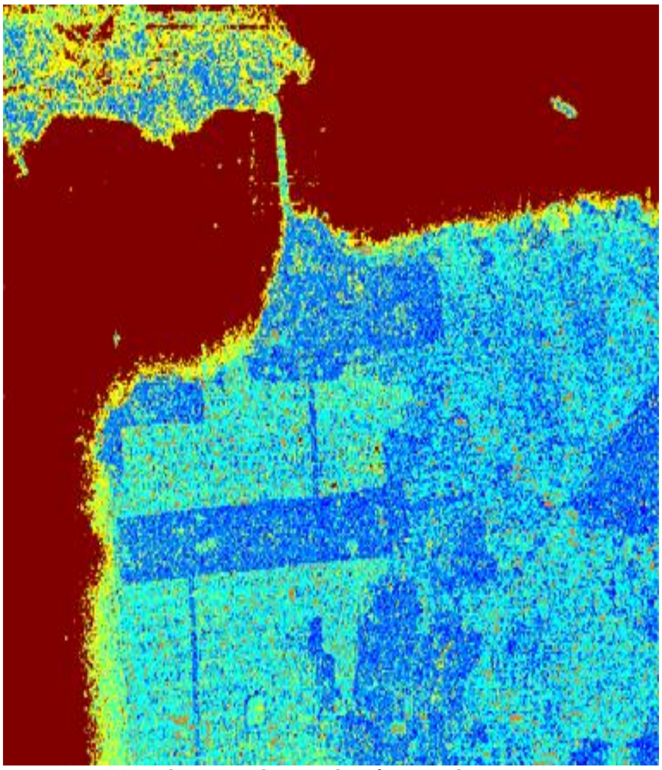


Fig(a). NASA/JPL AIRSAR L-band data of San Francisco

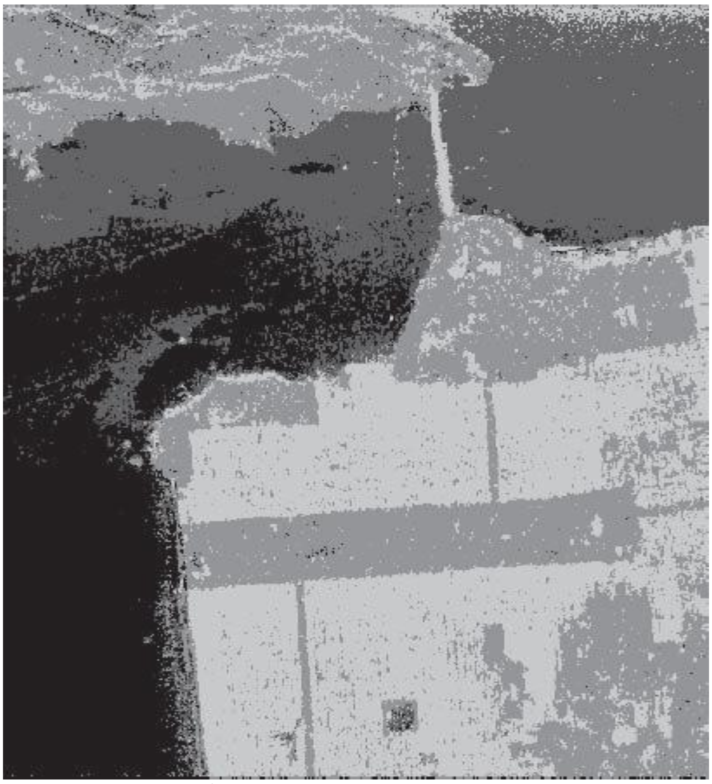
Fig(b) ML Classifier Results



Fig(c) Freeman Decomposition Results



Fig(e) Wishart Distribution Classifier Results



Fig(d). Adaboost Classifier Results

Fig(f).SVM Classifier Result;