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Unsupervised classification algorithm based on EM method for polarimetric SAR images

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ABSTRACT

In this work we develop an iterative classification algorithm using complex Gaussian mixture models for the polarimetric complex SAR data. It is a non supervised algorithm which does not require training data or an initial set of classes. Additionally, it determines the model order from data, which allows representing data structure with minimum complexity. The algorithm consists of four steps: initialization, model selection, refinement and smoothing. After a simple initialization stage, the EM algorithm is iteratively applied in the model selection step to compute the model order and an initial classification for the refinement step. The refinement step uses Classification EM (CEM) to reach the final classification and the smoothing stage improves the results by means of non-linear filtering. The algorithm is applied to both simulated and real Single Look Complex data of the EMISAR mission and compared with the Wishart classification method. We use confusion matrix and kappa statistic to make the comparison for simulated data whose ground-truth is known. We apply Davies–Bouldin index to compare both classifications for real data. The results obtained for both types of data validate our algorithm and show that its performance is comparable to Wishart's in terms of classification quality.
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1. Introduction

The Synthetic Aperture Radar (SAR) is a system that senses the earth surface and generates images for their study. Either airborne or spaceborne, the radar emits microwave frequency pulses and receives the reflected waves from the surface while travelling. Through a suitable processing, the information provided by these reflections is transformed into an image of the terrain, from which it is possible to study the terrain characteristics, such as vegetation, rugosity and moisture, among others.

In SAR signal processing, image classification is a very active and important topic (e.g., Uhlmann and Kiranyaz, 2014; Dabboor and Shokr, 2013; Sánchez-Lladó et al., 2011). It consists basically in transforming the scene image in a new image, where the pixels are organized in groups. Each group is defined by a specific feature shared by the data belonging to that group. This characteristic reveals structural information of the underlaying scene. In this context, we define a classifier as an algorithm that classifies every pixel in an image indicating to which group it belongs.

In this work, we are interested in techniques developed under a statistical framework. Then, pixels are sorted based on their distribution parameters which are estimated from the image data.

Due to the coherent nature of the radar signal, SAR images are affected by the speckle. This phenomenon is produced by the superposition of the reflected waves from irregular scattering elements situated at different viewing angles with respect to the incident wave. The size of those elements is comparable to the incident wavelength (Lee and Pottier, 2009, ch.4). The superposition causes constructive and destructive interference that affects the focused data. Because of this spurious effect, both the amplitude and the intensity of the complex signals tend to have very low signal to noise ratio (the ratio between mean and standard deviation) and classification becomes a difficult task. Therefore, most classification methods use data from amplitude or intensity, which can be averaged to increase the equivalent number of looks and, hence, increase the signal to noise ratio. However, the averaging process reduces the original resolution and details may be lost.

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For example, in Cloude and Pottier (1997) an unsupervised classification method is proposed based on the polarimetric target decomposition. This decomposition allows grouping the pixels according to the main reflection process (superficial, dipole or multiple reflections) and the randomness degree (entropy). In Lee et al. (1999) another unsupervised method is developed, based on the covariance matrix of the scattering vector and its Wishart probability density function. The latter algorithm uses the scheme proposed in Cloude and Pottier (1997) as initialization and then an iterative classification is performed until convergence is reached. In Fjortoft et al. (1999) segmentation is performed via edge detection using complex data, but no polarization information is used. All these methods require data averaging in order to obtain reliable results.

Iterative Expectation–Maximization (EM, Dempster et al., 1977) based methods have also been proposed to solve the classification problem. In Horta et al. (2008) the Stochastic EM algorithm is used along with the $\mathcal{G}_P^0$ model (Freitas et al., 2005) to describe homogeneous, heterogeneous and extremely heterogeneous terrains. More recently, in Kayabol and Zerubia (2013) an unsupervised classification method is proposed based on the Classification EM, where mixture models are used to describe amplitude and texture multilook data. In Yuan et al. (2006) and Dutta and Sarma (2014) the EM method with maximum a posteriori (MAP) classification is used along with a mixture Gaussian model for amplitude data. This classification assigns a pixel to a certain class when the posterior probability that the pixel belongs to that class is higher than the probability for the rest of the possible classes.

In most works dealing with Gaussian mixture models for classification, such models are used for describing real variables (amplitude or intensity), due to the possibility of signal to noise ratio enhancement via averaging, as we have already mentioned. On the other hand, averaging in the complex domain has no effect in the speckle because it does not increase the equivalent number of looks. In addition, in those approaches the model complexity is not optimized: the number of components in the mixture is pre-set or estimated by defining training zones in the image. This requires additional information of the terrain or the user's interpretation of information that may not be actually present in the dataset under study.

In this work, we develop an unsupervised segmentation algorithm using complex Gaussian mixture model for the polarimetric complex SAR data. It does not require previous information or training zone definitions, and the model complexity is estimated from the data through an iterative process. This allows to represent the data with a Gaussian mixture of a minimum number of components. The algorithm estimates the parameters of every component of the mixture and then classifies every pixel according to MAP criterion. The algorithm is divided into four stages: the first two steps perform the initialization and estimation of the model complexity using the EM algorithm and the Bayesian information criteria. The third step makes the pixel classification based on the Classification EM algorithm using the information of the previous steps as initialization. Finally, the last step applies a non-linear filter to smooth the resulting image.

It is worth noting that although we are using the complex target vector as data base, we are not using the related scattering matrix decomposition features to perform the classification since it is not useful at describing extended targets. The proposed classifier is based on the complex Gaussian mixture parameters as class descriptors, including the covariance matrix. This matrix is an adequate and widely used class descriptor since it condenses the polarimetric features of extended targets.

We evaluate our algorithm using both simulated and real data. It shows high performance, even though we do not use speckle reduction techniques in order to preserve resolution and the model simplicity. Moreover, the model selection step allows expressing the data set with minimum complexity preserving the structure of the original data, a characteristic that is not shared with conventional algorithms.

The paper proceeds as follows. In Section 2 we explain the mixture model used for the SAR data. In Section 3, we develop the four stages of our segmentation algorithm, and in Sections 4 and 5 we present the results for simulated and real data respectively. We evaluate the segmentation performance in terms of confusion matrix and the *kappa* statistic, and we compare it with the Wishart classification method. Finally, we summarize and analyze the results in Section 6.

2. Data model

In a polarimetric SAR system, each point on the field is represented by the complex scattering matrix $S \in \mathbb{C}^{2\times 2}$, whose elements indicate the relationship between incident and reflected fields for each polarization (Lee and Pottier, 2009, ch.3). The elements in S are re-arranged in the so-called target vector $k = [s_{hh}\ s_{hv}\ s_{vh}\ s_{vv}]^T$ (superscript T stands for vector transpose), which is the expression of a polarimetric SAR single look complex (SLC) data. Assuming the surface reached by the radar footprint is formed by homogeneous areas, a Gaussian model may be used (Frery et al., 2012). Since SAR data set contains information from a large piece of terrain, more than a single texture area needs to be modeled. Hence, we assign a complex Gaussian mixture model (CGMM) to the data, where each component of the mixture represents a particular feature of the underlying scene.

Let $k \in \mathbb{C}^d$ be a random variable representing the polarimetric SAR data. The general form of a mixture model with K classes is as follows:

$$f(k;\boldsymbol{\theta}) = \sum_{j=1}^{K} \omega_j f_j(k;\boldsymbol{\theta}_j), \tag{1}$$

where $f_1,\ldots,f_K$ are the K densities of probability of the model, each one representing a class. Every f_j has a set of parameters described by the vector $\boldsymbol{\theta}_j$. The coefficients w_j indicate the proportion of the jth component in the mixture, subject to the restrictions $\sum_{j=1}^{K}\omega_j = 1$ y $\omega_j \geqslant 0, j = 1\ldots K$. The vector parameter of the mixture is $\boldsymbol{\theta} = (\omega_1,\ldots,\omega_K,\boldsymbol{\theta}_1,\ldots,\boldsymbol{\theta}_K)$. Under the complex Gaussian assumptions, each term of (1) has the form $f_j(k;\boldsymbol{\theta}_j) = \pi^{-d}|\Sigma_j|^{-1}\exp(-(k-\boldsymbol{\mu}_j)^H\Sigma_j^{-1}(k-\boldsymbol{\mu}_j))$, where the mean $\boldsymbol{\mu}_j \in \mathbb{C}^d$ and the covariance $\Sigma_j \in \mathbb{C}^{d\times d}$ are the parameters $\boldsymbol{\theta}_j$ of the jth class.

The goal of our segmentation algorithm is to identify all classes present in the data set by estimating the model order K and the parameters of mixture $\boldsymbol{\theta}$ that better fit the data in the maximum likelihood sense. Each pair $(\omega_j,\boldsymbol{\theta}_j)$ describes a class, and in turn, identifies a polarimetric feature of the surface. Due to the model complexity, there exists no analytical solution for this optimization problem. Therefore, we use an iterative approach based on the EM algorithm to determine the model order and to estimate the parameters.

3. Algorithm structure

In this section, we describe the structure of the algorithm and its operation in detail. It is organized in the following four stages:

1. Initialization.
2. Model Selection.
3. Refinement.

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