Accepted Manuscript

Fully PolSAR image classification using machine learning techniques and reaction-diffusion systems

Luis Gomez, Luis Alvarez, Luis Mazorra, Alejandro C. Frery

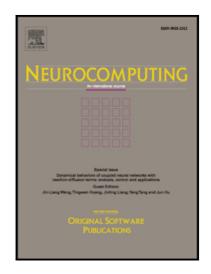
PII: S0925-2312(17)30546-5

DOI: 10.1016/j.neucom.2016.08.140

Reference: NEUCOM 18259

To appear in: Neurocomputing

Received date: 29 February 2016 Revised date: 8 August 2016 Accepted date: 30 August 2016



Please cite this article as: Luis Gomez, Luis Alvarez, Luis Mazorra, Alejandro C. Frery, Fully PolSAR image classification using machine learning techniques and reaction-diffusion systems, *Neurocomputing* (2017), doi: 10.1016/j.neucom.2016.08.140

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

ACCEPTED MANUSCRIPT

Fully PolSAR image classification using machine learning techniques and reaction-diffusion systems

Luis Gomez^a, Luis Alvarez^b, Luis Mazorra^b, Alejandro C. Frery^c

aCTIM. Dpto. de Ingeniería Electrónica y Automática
Universidad de Las Palmas de G.C.
Campus de Tafira, 35017, Spain
bCTIM. Dpto. de Informática y Sistemas
Universidad de Las Palmas de G.C.
Campus de Tafira, 35017, Spain
cLaboratório de Computação Científica e Análise Numérica
Instituto de Computação
Universidade Federal de Alagoas
Av. Lourival Melo Mota, s/n
57072-900 Maceió – AL, Brazil

Abstract

In this paper we study the problem of supervised Fully PolSAR (Polarimetric Synthetic Aperture Radar) image classification. We estimate a complex Wishart model distribution for each class using training data, and we use such models to design a new classification procedure based on a diffusion-reaction equation. The method relies on simultaneously filtering and classifying pixels within the image. The diffusion term smooths the patches within the image, and the reaction term tends to move the pixel values towards the closest (in the sense of stochastic distances) representative class. We present a detailed study of the method accuracy using both simulated and true data, and we provide optimum parameters for its use. We show that the proposed method outperforms the results obtained using maximum likelihood and usual stochastic distance classification methods.

Keywords: image processing, image analysis, classification, speckle, SAR polarimetry

1. Introduction

Classification is one of the most important techniques for image analysis. It aims at mapping each pixel into a class, so it transforms observations into information.

Classification can be performed using a variety of sources, mostly the spectral information (the observed value in each pixel), spatial or contextual information, and ancillary data (ground truth, for instance). The latter is usually only available in very restricted areas, from which training samples can be obtained.

The simplest available classification techniques rely only on pixel-wise information, i.e., on the observation in each coordinate: Isodata, Parallelepiped and Pointwise Maximum Likelihood are examples of these methods; cf. Ref. [1]. Arguably, the most successful techniques exploit both the spectral information and the context. This is mostly due to the fact that images exhibit a great deal of spatial redundancy, i.e., spatially neighboring pixels tend to be alike.

As an example of contextual classification one should mention techniques based on Markovian models. Geman and Geman [2] formulated the classification as an estimation problem and, as such, proposed a number of estimators and algorithms. These techniques rely on variations of the following idea: the class ξ in each coordinate should satisfy a criterion that, simultaneously, optimizes the pointwise spectral evidence and a contextual measure of smoothness, for example maximizing

$$\lambda f_{\mathcal{E}}(z(i,j)) + (1-\lambda)N(\xi,\partial_{ij}),\tag{1}$$

where $\lambda \in [0, 1]$ is the relative weight of the spectral evidence over the context, $f_{\xi}(z(i, j))$ is the likelihood of the observation z(i, j) in coordinate (i, j) with respect to the model characterized by the probability density function $f_{\xi}, \xi \in \{1, \dots, M\}$ is one of the M possible classes, and

Email addresses: luis.gomez@ulpgc.es (Luis Gomez), lalvarez@ctim.es (Luis Alvarez), lmazorra@ctim.es (Luis Mazorra), acfrery@ic.ufal.br (Alejandro C. Frery)

Download English Version:

https://daneshyari.com/en/article/4947238

Download Persian Version:

https://daneshyari.com/article/4947238

<u>Daneshyari.com</u>