South Asian Journal of Engineering and Technology Vol.2, No.17 (2016) 218–222

ISSN No: 2454-9614

Multivariate Statistical Model for Change Detection in Images with Image Classification

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Received: 12/11/2015, Revised: 21/12/2015 and Accepted: 12/03/2016

Abstract

This paper introduces a new statistical model for homogeneous images acquired by the same kind of sensor (e.g., two optical images) and heterogeneous images acquired by different sensors (e.g., optical and Synthetic Aperture Radar (SAR) images). The existing system gets the images at various time periods and detects the changes between the given images. The Expectation Maximization (EM) Algorithm is used for similarity measurement between the images. Initially the image can be derived into pixel-wise and the Joint distribution for pixel intensities can be carried out and it is used to remove the speckle noise. To measure the similarity between images the sliding window concept is applied. The proposed system introduces a new approach called Fuzzy C-means Clustering (FCM) Algorithm for similarity measurement between the images. Both low resolution and high resolution pixels are classified using Median Filter and are taken for speckle noise removal with different threshold values. Various regions such as land, water and other types are highlighted based on the RGB pixel values. Comparison between old and new images of same area is carried out and difference in their percentage is found out. The performance measures have been measured between the existing and the proposed system.

Keywords: Optical Images, SAR Images, Image analysis, Change detection, Remote sensing, EM Algorithm, Multi temporal images, Fuzzy C means Clustering Algorithm. **Reviewed by* **ICETSET'16** *organizing committee*

1. Introduction

Satellite remote sensing images are used to monitor the changes on the earth surface for various applications such as plantation monitoring, urban database updating, etc. This can be tracked by detecting changes between images acquired at different times and possibly by different kinds of sensors. To achieve this, different sensors have been investigated namely Optical, Synthetic Aperture Radars (SAR) or Multi-Spectral Sensors. Optical sensors provide high resolution images. Whereas SAR sensors can be acquired even at night or under bad weather conditions and thus are more rapidly available in emergency situations. These sensors used to detect the changes at different times and different situations like natural disasters such as floods, volcano eruptions or earthquakes. In this paper we propose a new flexible change detection strategy capable of dealing with homogeneous and heterogeneous sensors (with a specific attention to detecting changes between optical and SAR images). In order to reduce the effect of noise and account for the spatial correlation present in most remote sensing images, a common approach used in image analysis is to consider groups of pixels contained in a sliding window. The distribution of these groups of pixels is clearly interesting for many image processing applications. These applications include change detection **[1-3],** image segmentation **[4, 5],** image registration **[1, 6]**, and database updating **[7].** Distributions that have been recently considered in the literature include bivariate gamma distributions for two Synthetic Aperture Radar (SAR) images **[1]** and bivariate Pearson distributions for heterogeneous optical and SAR images **[2].** However, change detection between images acquired by heterogeneous sensors has received much less attention in the literature than the optical/optical or radar/radar cases. One can cite the recent approach developed in which transforms one of the two images in order to obtain characteristics similar to the other image, using the theory of copulas. However, this method requires learning the appropriate copula using training samples and it is hardly generalizable to situations where more than two images are available. This paper proposes to define a new statistical model for multiple remote sensing images. We assume that we have observed a given scene through a set of D images denoted as {I1,…,ID} acquired by D sensors {S1,…,SD}. Each sensor has imaged the scene differently since a given sensor captures different physical properties of the objects involved in the scene. Moreover, the Kind of noise affecting these objects generally differs from one sensor to another. Consider as an example the case of two optical and SAR images (D = 2). The SAR images are very sensitive to the object edges whereas the colorimetric of a scene is clearly an important property contained in optical images. The noise affecting a given area of a homogenous SAR image is classically supposed to be a multiplicative speckle noise with gamma or Weibull distribution **[8].** Conversely, the noise affecting optical images has been considered as an additive Gaussian noise in many applications **[9].** This paper introduces a new flexible model allowing the physical and statistical properties of images to be captured. The proposed model is flexible in the sense that it can be used for homogeneous or heterogeneous images1 and for many kinds of sensors. Moreover, the model can be used to describe the pixel intensities contained in a sliding window. In many applications (e.g., change detection, registration), statistical models are used to describe the distribution of the pixels in a sliding window assuming that it remains the same for all pixels **[10].** In this case the window is called homogeneous. The model proposed in this paper takes into account possible variations of the statistical model inside the sliding window (due, for instance, to the presence of different objects). In this case the window is called heterogeneous. As an example, its application to change detection will be discussed at the end of this paper. The paper is organized as follows: Section 2 discusses about the related work of this paper. Conclusions are reported in Section 3.

2. Related Works

2.1 A New Statistical Model For Markovian Classfication Of Urban Areas In High-Resolution Sar Images - Celine Tison, Jeanmarie Nicolas, Florence Tupin, And Henri Maitre

In this paper, propose a classification method suitable for high-resolution synthetic aperture radar (SAR) images over urban areas. When processing SAR images, there is a strong need for statistical models of scattering to take into account multiplicative noise and high dynamics. For instance, the classification processes need to be based on the use of statistics. Our main contribution is the choice of an accurate model for high resolution SAR images over urban areas and its use in a Markovian classification algorithm. Clutter in SAR images becomes non-Gaussian when the resolution is high or when the area is man-made. Many models have been proposed to fit with non-Gaussian scattering statistics (Weibull, Log-normal, Nakagami–Rice, etc.), but none of them is flexible enough to model all kinds of surfaces in our context. As a consequence, we use a mathematical model that relies on the Fisher distribution and the log-moment estimation and which is relevant for one look data. This estimation method is based on the second-kind statistics, which are detailed in the paper. We also prove its accuracy for urban areas at high resolution. The quality of the classification that is obtained by mixing this model and Markovian segmentation is high and enables us to distinguish between ground, buildings, and vegetation. The classification method presented in this paper, classes are discriminated based on their statistical properties, which require accurate statistical models. However, the well-known model of fully develop speckle and the many derived models that are based on the hypothesis of a large amount of random reflectors per resolution cell tend to fail when applied to urban areas: these models are better suited to natural areas and low resolution rather than to urban areas and high resolution, because of the underlying assumptions of a large number of almost identical targets scattered over the pixel, and the hypothesis of a resolution cell with large dimensions compared to the wavelength. Increasing the resolution implies a reduction of the number of reflectors per resolution cell. In such conditions, the probability of having heterogeneous surfaces with one or a few predominant reflectors increases, while the probability of having many similar diffusers reduces. When the resolution cell is about the size of the small man-made objects that cover the scene, the hypothesis of fully developed speckle is no longer valid.

2.2 Automatic Analysis of the Difference Image for Unsupervised Change Detection - Lorenzo BRUZZONE and Diego Fernandez PRIETO

One of the main problems related to unsupervised change detection methods based on the “difference image” lies in the lack of efficient automatic techniques for discriminating between changed and unchanged pixels in the difference image. Such discrimination is usually performed by using empirical strategies or manual trialand-error procedures, which affect both the accuracy and the reliability of the change detection process. To overcome such drawbacks, in this paper, we propose two automatic techniques (based on the Bayes theory) for the analysis of the difference image. One allows an automatic selection of the decision threshold that minimizes the overall change detection error probability under the assumption that pixels in difference image are independent of one another. The other analyzes the difference image by considering the spatial-contextual information included in the neighborhood of each pixel. In particular, an approach based on Markov Random Fields (MRF's) that exploits inter pixel class dependency contexts is presented. Both proposed techniques require the knowledge of the statistical distributions of the changed and unchanged pixels in the difference image. To perform an unsupervised estimation of the statistical terms that characterize these distributions, we propose an iterative method based on the Expectation- Maximization (EM) algorithm. Experimental results confirm the effectiveness of both proposed techniques. In this paper, focus on one of the most widely used types of unsupervised change detection techniques, which are based on the so-called "difference image". These techniques process the two multi spectral images acquired at two different dates (or vegetation indexes, principal components etc., derived from such images) in order to generate a further image. The computed difference image is such that the values of the pixels associated with land cover changes present values significantly different from those of the pixels associated with unchanged areas. Changes are then identified by analyzing (e.g., thresholding) the difference image. For example, the univariate image differencing technique generates the difference image by subtracting, pixel by pixel, a single spectral band of the two multispectral images under analysis. The choice of the spectral band depends on the specific type of change to be detected. An analogous concept is applied by the widely used change vector analysis (CVA) technique. In this case, several spectral channels are used at each time. For each pair of corresponding pixels, a "spectral change vector" is computed as the difference between the feature vectors at the two times. Then, the pixel values in the difference image are associated with the modules of the spectral change vectors. It follows that unchanged pixels present small gray-level values, whereas changed pixels present rather large values. Other techniques, like image rationing, produce the difference image by computing the ratio, instead of the difference, between multi temporal images.

3. Conclusion

This paper introduced a new statistical model to describe the distribution of any number of homogeneous and heterogeneous images independently of the kind of sensors used to obtain these images. The proposed model was expressed as a mixture of multi-dimensional distributions whose parameters can be estimated by the Fuzzy C-means Clustering algorithm. This mixture of distributions can be used to determine standard similarity measures such as the mutual information and is thus interesting for many potential applications. As an example, the model was successfully applied to the detection of changes between Optical and Synthetic Aperture Radar images. However, it could be interesting for many other applications such as image registration, image indexing or image classification. Also the performance measure between existing and proposed system has been discussed. Moreover, further work should be conducted to validate the proposed model on a larger dataset containing homogeneous and heterogeneous images.

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