Chapter 28
Unsupervised Segmentation of Remote Sensing Images Using FD Based Texture Analysis Model and ISODATA

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ABSTRACT

In this paper, an unsupervised segmentation methodology is proposed for remotely sensed images by using Fractional Differential (FD) based texture analysis model and Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA). Essentially, image segmentation is used to assign unique class labels to different regions of an image. In this work, it is transformed into texture segmentation by signifying each class label as a unique texture class. The FD based texture analysis model is suggested for texture feature extraction from images and ISODATA is used for segmentation. The proposed methodology was first implemented on artificial target images and then on remote sensing images from Google Earth. The results of the proposed methodology are compared with those of the other texture analysis methods such as LBP (Local Binary Pattern) and NBP (Neighbors based Binary Pattern) by visual inspection as well as using classification measures derived from confusion matrix. It is justified that the proposed methodology outperforms LBP and NBP methods.

INTRODUCTION

Image segmentation is the process of subdividing an image into multiple regions. In other words, a label could be assigned to each pixel in the image such that pixels with the same label share a particular characteristic. Especially, in this work, each image region is assigned with a unique label representing a texture class. It is always true that low level image analysis that is based on classified image regions is

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more expressive than the one based on individual pixels. Hence, image segmentation is found by many researchers to be the most significant task for precise image interpretation (Sezgin, 2004).

Most of the conventional methods being adopted for image segmentation (Roy, 2014; Lu, 2007) depend on spectral features of an image, and they may lead to wrong segmentation, particularly in case of remotely sensed images. Therefore, image spatial features are preferred over spectral features for segmentation. It is noticed that texture, one of the spatial features, is contained in most of the images of natural scenes, ragged or worn surfaces of many objects and particularly in remote sensing images. Hence, the texture features are expected to provide a significant contribution for image segmentation (Haralick, 1973; Chen, 1995; Ojala, 2001; Li, 2003; Liu, 2006; Ranjan, 2014). It is also found that texture feature based segmentation is found to be more appropriate in many of the computer vision applications such as remote sensing (Chakraborty, 2012; Tsai, 2005; Roy, 2014; Cheng, 2013), defect detection in industrial applications (Xie, 2008; Iyer, 2014), medical imaging (Hajar Danesh, 2014) and content based image retrieval (Yue, 2011; Zhang, 2000).

In common, texture based image segmentation is found to be a challenging task primarily because there is no unique description existing for texture in the literature. However, the texture could possibly be described as recurrences of local neighborhood structures, but the description that texture is a function of spatial variation of pixel intensities is found to be more appropriate (SKLANSKY, 1978). Usually, texture based image segmentation is accomplished in two phases. First, texture features are extracted from images and represented as quantitative features using an appropriate texture analysis method. As a next step, segmentation is performed based on the texture features extracted. A huge number of texture analysis methods have been proposed in the literature and few of them are reviewed below:

In Gray Level Co-occurrence Matrix (GLCM) method (Haralick, 1973; Tsai, 2005), the texture is characterized by putting the probability density function of different pixel pairs in matrices. As per (He, 1990), texture is represented as a texture number in overlapping 3x3 regions and then by the frequency of these numbers for the whole image. With (Haralick, 1973) and (He, 1990), the number of components representing texture feature is more and hence the classification process becomes tedious.

A texture analysis method was suggested in transform domain (Chang, 1993), which is based on the observation that a large class of natural textures can be modelled as quasi-periodic signals. This method was hypothetically well supported, but, experimental justification was not sufficient. In (Yoshimura, 1997), segmentation of textured images was performed with edge detection that is based on texture feature variation in small image regions. However, in this method, the texture characterization process needed to be improved.

Some of the texture characterization methods are proposed based on various mathematical concepts such as partial differential equations and functional minimization (Vese, 2003), LU-transform (Targhi, 2006) and auto-correlation coefficients (Karthikeyan, 2012).

Recently, texture extraction methodologies have been proposed applying new strategies. Some of them are given below. Texture descriptors are proposed using neural network features (Cimpoi, Maji, Kokkinos et al., 2015). A texture segmentation methodology was framed based on the process of factorization of feature matrix, where local spectral histograms are used as features (Yuan, 2015). The feasibility of graph entropies to be used as texture descriptors for image segmentation is analysed in (Welk, 2015). Entropy based graph indices are formed as edge–weighted pixel graphs from within the morphological amoebas as structuring elements.

In (Tirandaz, 2016), the segmentation of SAR images is performed by designing a kernel function based on curvelet coefficient energy and by unsupervised spectral regression method. The texture fea-