

## Chapter 29

# Remote Sensing Image Classification Using Fuzzy–PSO Hybrid Approach

**Anasua Sarkar**

*Government College of Engineering and Leather Technology, India*

**Rajib Das**

*Jadavpur University, India*

### ABSTRACT

*Pixel classification among overlapping land cover regions in remote sensing imagery is a challenging task. Detection of uncertainty and vagueness are always key features for classifying mixed pixels. This chapter proposes an approach for pixel classification using hybrid approach of Fuzzy C-Means and Particle Swarm Optimization methods. This new unsupervised algorithm is able to identify clusters utilizing particle swarm optimization based on fuzzy membership values. This approach addresses overlapping regions in remote sensing images by uncertainties using fuzzy set membership values. PSO is a population-based stochastic optimization technique inspired from the social behavior of bird flocks. The authors demonstrate the algorithm for segmenting a LANDSAT image of Shanghai. The newly developed algorithm is compared with FCM and K-Means algorithms. The new algorithm-generated clustered regions are verified with the available ground truth knowledge. The validity and statistical analysis are performed to demonstrate the superior performance of the new algorithm with K-Means and FCM algorithms.*

### INTRODUCTION

Remote sensing is defined as the art and science of obtaining information about an object without being in direct physical contact with the object by Cogalton and Green in 1999 (Cogalton, 1999). Several methods exist for classifying pixels into known classes (for example, an urban area or turbid water) in remote sensing images. Mathematically, a remote sensing image can be defined as a set,

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$$\mathcal{P} = \{p_{ijk} | 1 \leq i \leq r, 1 \leq j \leq s, 1 \leq k \leq n\} \quad (1)$$

of  $r \times s \times n$  information units for pixels, where  $p_{ij} \in \{p_{ij1}, p_{ij2}, \dots, p_{ijk}\}$  is the set of spectral band values for  $n$  bands associated with the pixel of coordinate  $(i, j)$ . In order to find homogeneous regions in the image we model this image by fuzzy sets, that considers both the spatial image objects and the imprecision attached to them.

Let us denote the space on which the remote sensing image is defined by  $\mathcal{P}$  (usually  $\mathbb{R}^n$  or  $\mathbb{Z}^n$ ). We denote the points of  $\mathcal{P}$  (pixels or voxels) as the spatial variables  $x, y$ . Let  $d_p(x, y)$  denotes the spatial distance between two pixels  $\{x, y\} \in \mathcal{P}$ . In several earlier works on remote sensing,  $d_p$  is taken as the Euclidean distance on  $\mathcal{P}$  (Maulik, 2012)(Bandyopadhyay, 2005).

A crisp object  $\mathcal{C}$  in the remote sensing image is a subset of  $\mathcal{P}$ ,  $\mathcal{C} \subseteq \mathcal{P}$ . Henceforth, a fuzzy object is defined as a fuzzy subset  $\mathcal{F}$  of  $\mathcal{P}$ ,  $\mathcal{F} \subseteq \mathcal{P}$ . This fuzzy object  $\mathcal{F}$  is defined bi-uniquely by its membership function,  $\mu_{\mathcal{F}}(x) \in (0, 1]$  is known as the membership function, which represents the membership degree of the point  $x$  to the fuzzy set  $\mathcal{F}$ . When the value of  $\mu_{\mathcal{F}}(x)$  is closer to 1, the degree of membership of  $x$  in  $\mathcal{F}$  will be higher. Such a representation allows for a direct mapping of mixed pixels in overlapping land cover regions in remote sensing images. Let  $\mathcal{F}$  denotes the set of all fuzzy sets defined on  $\mathcal{P}$ . For any two pixels  $x, y$ , we denote by  $d_{\mathcal{F}}(x, y)$  as their distance in fuzzy perspective. The definition of a new method utilizing the particle swarm movements over fuzzy membership matrix is the scope of this chapter.

Clustering is one unsupervised classification method based on maximum intra-class similarity and minimum inter-class similarity. Other already proposed clustering, which can be applied for pixel classification in remote sensing imagery are - self-organizing map (SOM) (Spang, 2003), K-Means clustering (Tavazoie, 2001)(Hoon, 2004), simulated annealing (Lukashin, 1999), graph theoretic approach (Xu, 1999), fuzzy c-means clustering (Dembele, 2003) and scattered object clustering (de Souto, 2008). Several other methods like clustering based on symmetry (Maulik, 2009)(Sarkar, 2009)(Sarkar1, 2009) (Bandyopadhyay, 2005), supervised multi-objective learning approach (Maulik, 2012), also may be applicable efficiently for detection of arbitrary shaped land cover regions in remote sensing imagery problem.

The membership functions of both rough sets and fuzzy sets also enable efficient handling of overlapping partitions. Therefore, recently rough set theory is being used for clustering (Bandyopadhyay, 2008) (Cordasco, 2007)(Gonzalez, 1992)(Dembele, 2003)(Qin, 2003). Lingras (Xu, 1999)(Dembele, 2003) (Qin, 2003) used rough set theory to develop interval representation of clusters. This model is useful when the clusters do not necessarily have crisp boundaries.

Fuzzy set theory is a methodology to illustrate how to handle uncertainty and imprecise information in a difficult condition. The fuzzy models are normally used in land coverage detection of remote sensing image, pattern recognition and image processing (Bandyopadhyay, 2005)(Dave, 1989). Applying the concepts of fuzzy membership function (Wang, 1997)(Pappis, 1993), fuzzy clustering (Huang, 2008), fuzzy-rule based systems (Bardossy, 2002), fuzzy entropy (De Luca, 1972) and fuzzy integrals (Kumar, 1997) in algorithms, the remote sensing image identification becomes more feasible.

In the literature, earlier distances proposed comparing fuzzy membership functions do not include spatial information and therefore were not used in remote sensing (Chen, 1995) (Jain, 1995). The belongingness and non-belongingness of one pixel to one cluster can be utilized to detect as the approximated

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