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Research Article

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Fractional order Darwinian particle swarm optimization based segmentation of hyperspectral images

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ABSTRACT

Hyper spectral images are of high dimension. There are many number of data channels in a hyper spectral image. Segmentation of hyper spectral images is very difficult. In this paper a new segmentation technique for multispectral images is proposed. This paper introduces a concept that combined algorithm of FCM (fuzzy C) and fractional order Darwinian PSO can perform better in terms of classification accuracy. Fractional-order Darwinian particle swarm optimization (FODPSO) uses many sets of test data. Junction rate of particles are controlled by use of fractional derivative concept. Otsu problem is solved using this concept in remote sensing data. This paper classifies various features that are related to any remote sensing hyper spectral image. These features help us to analyse the images better for using in various applications.

Key words: FODPSO, Optimum thresholding, feature extraction

INTRODUCTION

Segmentation of an image partitions into various regions or parts. Each region is identified as objects with labels on each part or region. Image is classified in such a way that almost all the pixels in a region or part have similar spectral characteristics. Analysing the labels of a region provide better result than analysing every pixel of an image. Image segmentation [1] is regarded as an essential process in the study, elucidation, and understanding of images and is also widely used for image processing purposes such as classification and object recognition.

In PSO (Particle Swarm Optimisation), there are number of particles that move in space to find a global minimum. A drawback in PSO is that Particles may be trapped in wrong local optimum points. To overcome the problem of local minima, concept of Darwinian principle is introduced. This concept is termed as Darwinian PSO (DPSO).DPSO also follows the same concept as PSO except that there are many sets of test data. There are rules governing test data. DPSO is further extended to FODPSO using fractional calculus to manage the junction rate of the algorithm. This paper compares PSO, DPSO and FODPSO.

Image segmentation is an important area in study of images in remote sensing. To advance the classification, categorization [7] and segmentation are integrated. The process of assigning a pixel to a class is based upon the feature vector of the pixel and some characteristics from the segmentation step. To make this approach effective, an accurate segmentation [10] of the image is needed. A few methods for segmentation of multispectral and hyper spectral images have been introduced in the literature. All the regions are merged are based on the homogeneity.

Image segmentation [4[6] can be divided into four precise categories comprising of histogram-thresholding-based methods, texture analysis-based methods, clustering-based methods, and region based split and merging methods. Thresholding [2] segments the images into many numbers of clusters. There are two classes of thresholding techniques. They are optimal and property based thresholding. Optimal thresholding algorithms search for optimum thresholding levels .This makes the threshold classes on the histogram to attain its wanted characteristics. Objective functions are optimised to select thresholds. Property based thresholding spots the threshold level by calculating a few particular properties of the histogram. Property based thresholding are useful in case of multilevel thresholding as they are fast. Finding the number of threshold levels is difficult in these types of thresholding techniques.

Many research papers have considered multilevel thresholding problems. Bi-level thresholding is decreased to an optimization problem to find the threshold level **t** that increases σ_B^2 (to find various between classes) and reduces σ_W^2 (To find variance within classes).For two-level thresholding, the assessment of T^* is important and this must convince the condition

$$\max \ \sigma_B^2 ((T^*)) \ \text{where } 0 \le T^* < L \tag{1}$$

Where L is the maximum value of intensity level. This problem could be extended to *n*-level thresholding by satisfying

$$\max \ \sigma_B^2 (T^*1, T^*2, \ldots, T^*n-1) \tag{2}$$

Where $0 \le T^*1 < T^*2 < \cdots < T^*n-1 < L$.First way to determine the optimal sets of threshold levels is to perform a search. This search is based on Otsu criterion. The process of finding optimal level by search is easier but it has a drawback that it is computationally costly. To find n−1 optimal thresholds we need to find evaluations of fitness of n(L − n + 1)n−1 combinations of thresholds. This makes search method not applicable for finding n level thresholds. The process of finding n − 1 optimal thresholding levels for n-level image thresholding could be designed as a multidimensional optimization problem. Steps involved are

- FODPSO algorithm is used for image segmentation;
- Complex data sets are used to compare it with other methods
- Proposal of a new categorization approach based on the idea of the new segmentation method to improve the classification accuracy

EXPERIMENTAL SECTION

The routine assortment of an accurate optimum n-level threshold value is difficult for segmentation of remote sensing images. This paper formulates solution for segmentation of hyper spectral images [8].

Problem Formulation
Let us consider L levels of intensity in an image e.g. an image with three colour components RGB has the intensity levels with a range of {0, 1, 2, .. L − 1}. Then, a pixel can be defined as

$$p_i^C = \frac{h_i^C}{N} \sum_{i=0}^{L-1} p_i^C = 1 \tag{3}$$

Where i refers a specific intensity level, i.e., $0 \le i \le L - 1$;

C represents the component of the image, e.g. C={R, G, B} for an RGB image; *N* represents the total number of pixels in the image; and h_i^C denotes the number of pixels for the respective intensity level i in component C. In other words, h_i^C denotes an image histogram for each component C, which can be normalized and considered as the probability distribution p_i^C. The whole mean (i.e., joint mean) of every component of the image can be simply designed as

$$\mu_T^C = \sum_{i=0}^{L-1} i p_i^C = 1 \tag{4}$$

The *n*-level thresholding presents $n - 1$ threshold levels. t_j^C,$j = 1, \ldots\ldots n - 1$, and is calculated as F^C(x,y) where *x* and *y* are the width (*W*) and height (*H*) of the pixel of the image of size $H \times W$ denoted by $fc(x, y)$ with *L* intensity levels for each component. Pixels of the image are divided as n classes $Dc1, \ldots, Dcn$, These classes denote variety of objects or still detailed features .These features include topological characteristics. The probabilities of occurrence w_j^c of classes $Dc1 \ldots\ldots\ldots, Dcn$ are given by

$$w_j^C=\begin{cases}\sum_{i=0}^{t_j^C}\frac{p_i^C}{w_j^C q}, & j=1\\ \sum_{i=t_{j-1}^C}^{t_j^C}+1\frac{p_i^C}{w_j^C}, & 1<j<n\\ \sum_{i=t_{j-1}^C}^{L-1}+1\frac{p_i^C}{w_j^C}, & j=n\end{cases} \tag{5}$$

The easiest method of finding the thresholding level increases the variance between classes. Between class variance can be defined as

$$\sigma_B^{C^2}=\sum_{j-1}^{N} w_j^C\,(\mu_j^C-\mu_T^C)^2 \tag{6}$$

where j denotes a specific class in such a way that w_j^C is the probability of occurrence and μ_j^C is the mean of class j.

The n-level thresholding problem is reduced to an optimization problem. The Fitness value of each image component C is defined as

$$\phi^C=\max_{1<t_i^{L-1}}\sigma_B^{C^2}\,(t_j^C) \tag{7}$$

The optimisation problem becomes more complex with increasing thresholding levels.

General Approach

PSO1 algorithm was initially proposed by Eberhart and Kennedy in 1995. The PSO algorithm uses the swarm intelligence idea. Swarm intelligence is properties in which various particles that interact among themselves make consistent global efficient patterns. The concepts of PSO, the DPSO and the FOPSO are combined to produce FODPSO. In FODPSO swarms struggle using Darwin's survival-of-the-fittest principles and fractional calculus is used to control the junction rate of the algorithm. By the use of these principles the particles are avoided from the problem of local minima. Several PSO algorithms are run simultaneously. First local optimum is searched in a particular area. Then if it is not found, it is simply discarded and local optima is searched in some other areas. Swarms [3] that survive each test of finding local optima points are given an increased life period and particles that do not pass get a reduction in lifetime.

Every particle a within every unlike group (swarm) s shifts in a many dimensional space based on position ($xa[t]$), $0 \le xa[t] \le L-1$, and velocity ($va[t]$). Local best ($\breve{x}a[t]$) and global best ($\breve{g}a[t]$) information decide the position and location value. When the recent velocity is found, weights are given to the coefficients w, $\rho1$, and $\rho2$. These coefficients control the inertial influence, i.e., according to "the globally best" and "the locally best," respectively. Typically, the inertial influence is set to a value slightly less than 1. $\rho1$ and $\rho2$ are constant integer values, which represent "cognitive" and "social" components. Results can be varied based on the values assigned to these parameters. Based on the application and the description of the predicament, changing the parameter values properly will lead to better results. The parameters $r1$ and $r2$ are random vectors, with each component generally a uniform random number between 0 and 1. The target is to multiply a new random component for each velocity dimension other than multiplying the same component with the velocity dimension of each particle. Values of α particle affect the inertial particles. Smaller α value of the particles disregards their earlier activities, thus avoiding the system dynamics and there is a problem of getting caught in local optima points. On the contrary the particles with a large α allow finding of new solutions and increases the long-term performance (i.e., exploration behaviour). If the exploration level is too high, then the process of finding global minima takes too much time.

Table 1. Computational and Memory Complexities of PSO, DPSO, AND FODPSO

Complexity	PSO	DPSO	FODPSO
Memory	O(C)	O(C)	O(4C)
Computational	O(nN^p)	O(n$\sum_{\forall s} N^S$)	O(n$\sum_{\forall s} N^S$)

The memory complexity of the FODPSO is more than DPSO and PSO. FODPSO has memory properties related to the fractional extension. Due to the truncation order of the approximate fractional derivative, particle's velocity is tracked depending on the number of components C of the image. The computational complexity of the three algorithms will increase with the number of desired thresholds n. The PSO algorithm depends on the number of particles NP within the inhabitant particles, the DPSO and FODPSO are based on the accumulated number of particles within each swarm.

Algorithm Evaluation

The calculation time and the fitness value determine the performance of the algorithm. Since the data is large, the performance of the algorithm is restricted to a greater level. As hyperspectral [5][9] images are large in size, a new fast and effective algorithm is mostly preferable. Use of a high-speed algorithm is an important aim in real time applications. Analysis of processing time of CPU and the fitness value seems to be really important to illustrate the efficiency of the proposed method. Similarly the steadiness of diverse methods should be assessed by use of proper index such as standard deviation value. The capability of the conventional PSO- based segmentation has already been matched up to with other thresholding-based methods such as GA-based algorithms. The PSO-based method proves to better in terms of fitness value and CPU processing time.

RESULTS AND DISCUSSION

The following are the steps that we perform for segmentation of a hyper spectral image in MATLAB using FODPSO. This involves

- Calculation of histogram for each spectral band
- Mapping
- Classification of various parameters

Multispectral Input Image

Figure 1: Input data for segmentation using FODPSO

Histogram Calculation

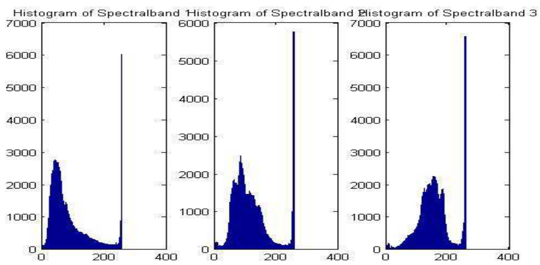

Figure 2.Histogram for each spectral band

Figure 3. Spectral band of the given image

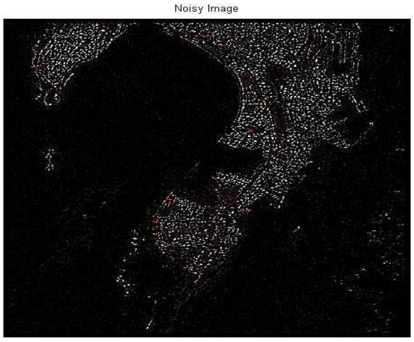

Figure 4. .Noisy Present in the image

Mapping and segmentation

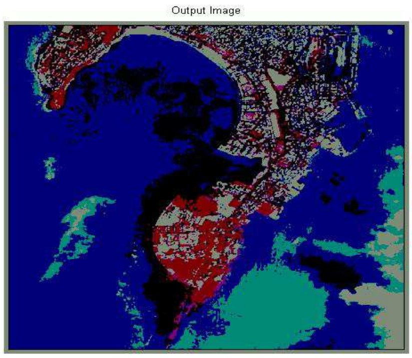

Figure 5. Output segmented image

Parameter calculation of FODPSO

Table 2. Parameter calculation of FODPSO

S.No	Parameters	Value
1	autocorrelation	[3.6049 3.5788]
2	Contrast	[0.8838 0.9371]
3	Entropy	[0.8014 0.8127]
4	Energy	[0.5877 0.5829]
5	Sum Average	[3.2187 3.2190]
6	Sum Variance	[11.1203 1.0332]
7	Sum Entropy	[0.7334 0.7406]
8	Difference variance	[0.8838 0.9371]
9	Difference entropy	[0.3211 0.3341]
10	Maximum Probability	[0.7478 0.7448]
11	Inverse difference normalized	[0.9732 0.9716]
12	Inverse difference moment normalized	[0.9879 0.9872]

CONCLUSION

In this paper, a fresh multilevel thresholding segmentation method has been planned for grouping the pixels of multi- spectral and hyperspectral images into diverse homogenous regions. The new method is based on FODPSO which is used in finding the optimal set of threshold values and uses many swarms of test solutions which may exist at any time. In the FODPSO, each swarm individually performs just like an ordinary (PSO) algorithm with a set of rules governing the collection of swarms that are designed to simulate natural selection. Moreover, the concept of fraction a derivative is used to control the convergence rate of particles. Experimental results compare the FODPSO with the classical PSO and DPSO within multilevel segmentation problems on remote sensing images from different points of view such as CPU time and corresponding fitness value.

REFERENCES

[1] P Ghamisi;MS Couceiro; JA Benediktsson; NMF Ferreira, ,*Expert Syst. Appl*., **2012**, 39(16), 12407– 12417.
[2] M Sezgin; B Sankur,*J. Electron. Imag*., **2004**,13(1),146–168.
[3] P Ghamisi; MS Couceiro; NMF Ferreira; L Kumar, in Proc. *IEEE IGARSS*, **2012**, 4295– 4298.

[4]Y Tarabalka; J Chanussot; JA Benediktsson, *Pattern Recognit*., **2010**,43(7), 2367–2379. [5] M Fauvel; Y Tarabalka; JA Benediktsson;J Chanussot;JC Tilton, *Proc. IEEE*,**2013**,101(3), 652–675.
[6] A Darwish; K Leukert; W Reinhardt, in Proc. IGARSS, **2003**, vol. 3, pp. 2039–2041.
[7] J Tilton, in Proc. IEEE Workshop *Adv. Tech. Anal. Remotely Sensed Data*, **2003**, 60–69.
[8] M Pesaresi; JA Benediktsson,*IEEE Trans. Geosci. Remote Sens*., **2001**,39(2),309–320.
[9] G Noyel; JAngulo;D Jeulin, *Image Anal. Stereol*.,**2007**, 26(1), 101–109.
[10] HG Akcay; S Aksoy, *IEEE Trans. Geosci. Remote Sens*,**2008**,46(7),2097–2111.