A New Approach Based On FODPSO for Segmentation and Classification of Hyperspectral Image

(E.Venkatesh)[1] (Smt.S.Swarna Latha)[2]

[1](Pg Scholar, Dept Of Electronics & Communication Engineering, Svu Engineering College, Tirupati
[2](Associate Professor, Dept Of Electronics &Communication engineering, Svu Engineering College, Tirupati)

***Abstract*—*Hyperspectral remote sensing images contain hundreds of data channels. Due to the high dimensionality of the hyperspectral data, it is difficult to design accurate and efficient image segmentation algorithms for such imagery. Here we introduce a novel algorithm for the segmentation of hyperspectral and multispectral images. This algorithm is based on fractional-order Darwinian particle swarm optimization (FODPSO) which exploits many swarms of test solutions that may exist at any time using Genetic Algorithm(GA). The Genetic Algorithm efficiently locate the global maximum in a search space and solves the problem of parameter selection in image segmentation .In addition to this a 2D adaptive log filter is proposed to denoise the hyperspectral image in order to remove the speckle noise and an adaptive Histogram coherence enhancement technique is used to improve the quality of the hyperspectral image. Here FCM is used to increase the clustering speed. Furthermore, the proposed clustering approach is combined with SVM classification to accurately classify hyperspectral images. The experimental results reveal that our proposed method is better compare to the state-of-art of criteria.*

Keywords—*FODPSO,2D adaptive log filter, FCM, SVM ,Genetic Algorithm*

I. INTRODUCTION

Hyperspectral imaging systems have gained a great attention from researchers in the past few years. These systems use sensors, which acquire data mostly from the visible through the middle infrared wavelength ranges and can simultaneosusly capture hundreds of (narrow) spectral channels from the same area on the surface of the Earth. Thanks to the detailed spectral information provided by hyperspectral sensors, the possibility of accurately discriminating materials of interest with an increased classification accuracy is increased. Furthermore, with respect to advances in hyperspectral imaging systems, the spatial resolution of recently operated sensors is getting finer, which enables analysis of small spatial structures in images. Without any doubt, classification (or mapping) can be considered as the backbone of most image interpretation in remote sensing. In general, supervised classification approaches classify input data by considering the spectral information (e.g., intensity value of each pixel for grayscale images or intensity vector for RGB or high-dimensional images) of the data to produce a classification map in order to discriminate different classes of interest, by using a set of representative samples for each class, referred to as training samples. This way, by using a combination of training followed by classification, maps are produced from imagery. However, most of the existing classification techniques have been developed for the analysis of multispectral images, and consequently, they are not usually efficient for the classification of hyperspectral images, which can provide a detailed spectral information.

A. Applications

Ecological science: Hyperspectral images are used to estimate biomass and carbon, biodiversity in denseforest zones and can be used to study land cover changes.
Geological science: It is possible to recover physico-chemical mineral properties such as composition and abundance.
Mineralogy: By using hyperspectral data, not only a wide range of minerals can be identified but also their

relation to the presence of valuable minerals can be understood. Currently, researchers are investigating the effect of oil and gas leakages from pipelines and natural wells on the spectral signatures of vegetation.

Hydrological science :Hyperspectral imagery is taken into account to determine changes in wetland characteristics. Moreover, water quality, estuarine environments and coastal zones can be investigated by using hyperspectral images as well.

Precision agriculture: Hyperspectral data are considered as a powerful tool in order to classify agricultural classes and to extract nitrogen content for the purpose of precision agriculture.

Military applications: The rich spectral-spatial information of hyperspectral data can be also used for target detection. The intrinsic properties of hyperspectral images need to be addressed specifically because conventional algorithms made for multispectral images do not adapt well to the analysis of hyperspectral images.

The rest of this paper is organized as follows. Section II first reviews existing method. Our proposed method is described in Section III. Then experimental results are reported in Section IV to demonstrate the superior performance of our framework. Finally, conclusions are presented in Section V.

II. EXISTING METHOD

The existing algorithm is produced through combining PSO algorithm with one of region-based image segmentation method. The algorithm performs segmentation of an Image with respect to a set ofpoints known as seeds.

Two problems are related with this method, the first one is the choice ofthe similarity criteria of pixels in regions and the secondproblem is how to select the seeds.

Particle swarm optimization (PSO) has roots in two main component methodologies. Perhaps more obvious are its ties to artificial life (A-life) in general, and to bird flocking, fish schooling, and swarming theory in particular. It is also related, however, to evolutionary Computation, and has ties to both genetic algorithms and evolution strategies.

PSO is unlike a genetic algorithm, however, in that each potential solution is also assigned a randomized velocity, and the potential solutions, called particles, are then “flown” through hyperspace. Each particle keeps track of its coordinates in hyperspace which are associated with the best solution (fitness) it has achieved so far. (The value of that fitness is also stored.) This value is called pbest. Another “best” value is also tracked.

The “global” version of the particle swarm optimizer keeps track of the overall best value, and its location, obtained thus far by any particle in the population; this is called gbest.

The particle swarm optimization concept consists of, at each time step, changing the velocity (accelerating) each particle toward its pbest and gbest (global version). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward pbest and gbest.

A. Disadvantages

1. The similarity criteria, ie, the best similarity difference between the pixel intensity and region mean value is improper. This problem leads to segmentation of the Non Region of Interest pixels.
2. The seeded region growing approach to image segmentation is to segment an image into regions with respect to a set of n seed regions. But the n value is not properly selected. The n value is the approximated only. So the accuracy of the segmentation is poor.
3. The region growing segmentation is not preferred for its limited range of applications and automatic features are not having accurate values
4. Preprocessing experiments are needed to find which type of filtering will be more beneficial. This increases the effect of the speckle noise and Gaussian noise the hyper-spectral Images.
5. This algorithm fully depends on the intensity of the image not the shape and texture. So the accuracy and sensitivity is low.

III. PROPOSED METHOD

In the proposed method, initially, the input hyperspectral information set is grouped by the novel clustering method (FODPSOFCM). In similar way, the input hyperspectral information is classified by

SVM. Finally, the outputs of the SVM and FODPSO-FCM are incorporated through a majority voting process, from which the final classification map is formed using GA. By doing this, it is likely to take benefit of SVM which can handle high-dimensional information with a limited number of training samples and the proposed clustering method which is based on fuzzy theory and can mold gradual changes between diverse classes.

In order to overcome the drawback of traditional PSO We proposed FODPSO-FCM for clustering.

A. Pre-Processing:

Pre-processing steps include geometric correction, destripping, subsetting of the images according to region of interest, noise and dimensionality reduction and finally atmospheric correction. Here to reduce the noise we have used 2D Adaptive Log Filter.

Generally speckle noise is commonly found in synthetic aperture radar images, satellite images and hyperspectral images. To remove speckle noise we proposed 2D Adaptive Log Filter.Noise level is measured by the standard deviation.

After applying the filter image enhancement is done by adaptive Histogram coherence enhancement to improve the contrast of the image so that the visibility of image will be very clear. It differs from the ordinary histogram equalization.

The proposed method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast of an image and bringing out more detail.

B.Fractional Order Darwinian Particle Swarm Optimization (FODPSO)-FCM:

Fractional calculus has attracted the attention of several researchers being applied in various scientific fields such as engineering, computational mathematics, fluid mechanics etc. The Grünwald–Letnikov definition based on the concept of fractional differential with fractional coefficient $\alpha \in C$ of a general signal.

The characteristics revealed by fractional calculus make this mathematical tool well suited to describe phenomena such as irreversibility and chaos because of its inherent memory property.

Moreover, the FO-DPSO may also be seen as a collection of FO-PSO"s as in which each swarm individually performs with some natural selection rules.

A swarm behavior can be divided into two activities: a) exploitation; and b) exploration. The first one is related with the convergence of the algorithm, thus allowing a good short-term performance. However, if the exploitation level is too high, then the algorithm may be stuck on local solutions. The second one is related with the diversification of the algorithm which allows exploring new solutions, thus improving the long-term performance. However, if the exploration level is too high, then the algorithm may take too much time to find the global solution. As first presented by Shi and Eberhart, the trade-off between exploitation and exploration in the classical PSO has been commonly handled by adjusting the inertia weight. A large inertia weight improves exploration activity while exploitation is improved using a small inertia weight. Since the FO-DPSO presents a fractional calculus.

Strategy to control the convergence of particles, the coefficient α needs to be defined in order to provide a high level of exploration while ensuring the global solution of the mission.If a new global solution is found, a new particle is spawned. If the swarm fails to find a fitter state in a defined number of steps, the particle is deleted.

C. Genetic Algorithm for Optimization:

Given a clearly defined problem to be solved and a bit string representation for candidate solutions, a simple GA works as follows:

1. Start with a randomly generated population of n l−bit chromosomes (candidate solutions to a problem).
2. Calculate the fitness $f(x)$ of each chromosome x in the population.
3. Repeat the following steps until n offspring have been created:

a. Select a pair of parent chromosomes from the current population, the probability of selection being an increasing function of fitness.

Selection is done "with replacement," meaning that the same chromosome can be selected more than once to become a parent.

b. With probability pc (the "crossover probability" or "crossover rate"), cross over the pair at a randomly chosen point (chosen with uniform probability) to form two offspring. If no crossover takes place, form two offspring that are exact copies of their respective parents.

c. Mutate the two offspring at each locus with probability pm (the mutation probability or mutation rate), and place the resulting chromosomes in the new population. If n is odd, one new population member can be discarded at random.

4. Replace the current population with the new population.
5. Go to step 2. Each iteration of this process is called a generation.

A GA is typically iterated for anywhere from 50 to 500 or more generations. The entire set of generations is called a run. At the end of a run there are often one or more highly fit chromosomes in the population. Since randomness plays a large role in each run, two runs with different random−number seeds will generally produce different detailed behaviors.

D. SVM Classifier:

The output of the FODPSO-FCM is combined with the SVM output to get the majority voting.The SVM is a supervised learning method. It is a goodtool for data analysis and classification. SVM classifier has a fast learning speed even in large data. SVM is used for two or more class classification problems. Support Vector Machine is based on the conception of decision planes.

A decision plane is one that separates between a set of items having dissimilar class memberships**.** The Classification and detection of information was done by using the Support Vector Machinetechnique. Classification is done to identify the classes present in the image. The use of SVM involves two basic steps of training and testing. This avoids under fitting: small training error and over fitting: small testing error.

It should be noted that the classification framework in this work has been only used for the evaluation of the capability of different clustering techniques and the main novelty of this paper goes to the proposition of the new clustering method.

E. Advantages

1. The best similarity difference between the pixel intensity and region mean value is properly given by the proposed algorithm. So the exact region of interest can be segmented.
2. The automatic feature extraction using Gray Level co-occurrence Matrix is possible which features are used for SVM classification.
3. The algorithm depend not only the intensity but also depend on the shape and texture. So the segmentation of the object and pixel is proper.
4. The proposed algorithm is applicable for both gray and RGB color space images.

IV.RESULTS

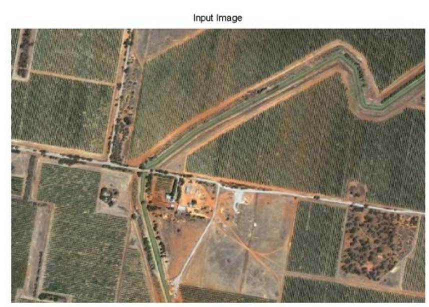

Fig1:Original image

Fig2: Hybrid Median Filtered Image

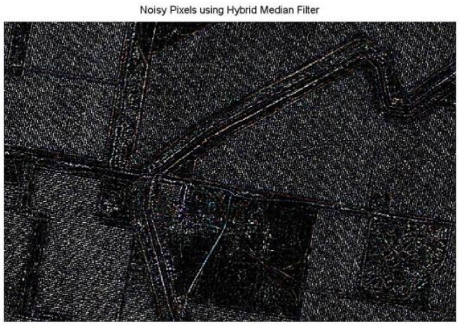

Fig3: Noisy Pixels Using Hybrid Median Filter

Fig4: Log Color Filter Image

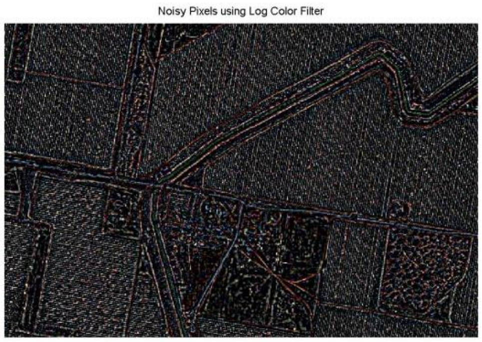

Fig5: Noisy Pixels Using Log Color Filter

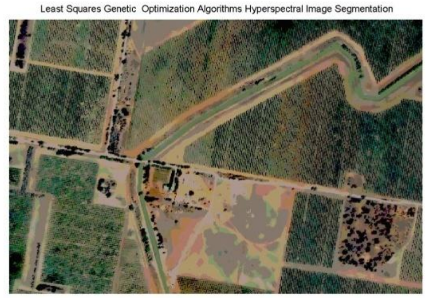

Fig6: Least Square Genetic Optimization

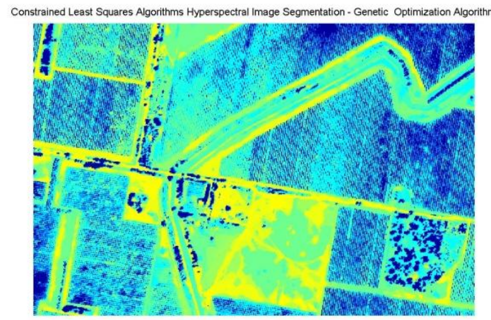

Fig7:Hybrid Last Square Genetic Image

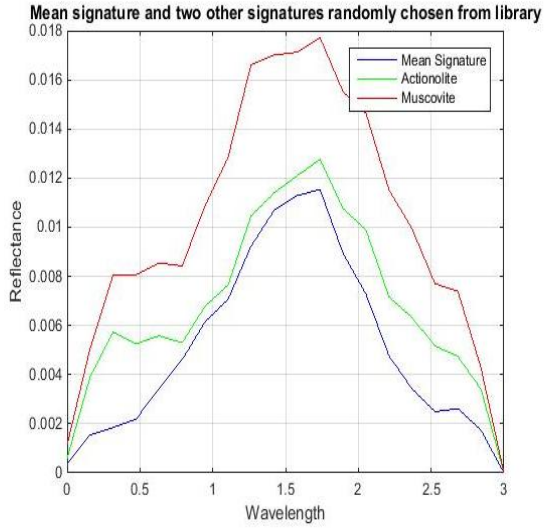

Fig8: Comparison Of Mean Signature, Actionolite, Muscovite

I. COMPARISON TABLE

METHODS	OA	Kappa	Time(s)
PSO	95.92	0.9546	3.59
FODPSO+GENETIC	97.79	0.9879	2.4

V.CONCLUSIONS

The proposed approach profits from a fractional calculus method FODPSO-FCM to improve the convergence rate of the traditional FCM, while, at the same time, it benefits from the same natural choice mechanism as the original PSO to evade stagnation approximately limited optima. Then we used the genetic algorithm for the optimization to solve the drawback FODPSO.Then, the proposed fuzzy clustering method is used to progress the classification of hyperspectral images with SVM. It is well known that the SVM is able to proficientlycategorize high-dimensional data with limited samples.The experimental evaluation for two standard hyperspectral images demonstrates that the performance of the proposed method, which uses a purely inspired behavior based on natural selection and noninteger convergence, results in a statistically significant improvement in terms of overall classification accuracy and kappa coefficient.

As a possible future work, the automatic selection of the number of clusters for complicated data sets and the new approach can be combined with Hidden Markov Random Field Model can be of interest.

ACKNOWLEDGEMENT

The prime author of the article Mr. E.Venkatesh studying MTech at SVU college of Engineering (SVUCE), Tirupati would like to thank to AICTE for providing the MTP stipend. One of the authors, Smt.S.Swarna Latha, Associate Professor, SVUCE would like to thank the officials of Department of SVUCE, for funding the Research projects at SV University, Tirupathi.

REFERNCES

[1] R. Duda, P. Hart, and D. Stork, *Pattern Classification*, 2nd ed. Hoboken, NJ, USA: Wiley, 2001.

[2] A. Dutta, "Fuzzy c-means classification of multispectral data incorporatingspatial contextual information by using Markov random field," M.S.
thesis, Geo informatics, ITC, 2009.

[3] J. Bezdek, *Fuzzy Mathematics in Pattern Classification*, 2nd ed. Hoboken,NJ, USA: Wiley, 1973.

[4] W. Wang, Y. Zhang, Y. Li, and X. Zhang, "The global fuzzy c-meansclustering algorithm," in*Intelligent Control and Automation*, vol. 1,pp. 3604–3607, 2006.

[5] J. Kennedy and R. Eberhart, "A new optimizer using particle swarm theory,"in *Proc. IEEE 6th Int. Symp. Micro Mach. Hum. Sci.*, 1995, vol. 34,no. 2008, pp. 39–43.

[6] M. S. Couceiro, R. P. Rocha, N. M. F. Ferreira, and J. A. T. Machado,"Introducing the fractional order darwinian PSO," *Signal Image VideoProcess.*, vol. 102, no. 1, pp. 8–16, 2007.

[7] P. Ghamisi, M. S. Couceiro, J. A. Benediktsson, and N. M. F. Ferreira,"An efficient method for segmentation of images based on fractional calculus
and natural selection," *Expert Syst. Appl.*, vol. 39, no. 16, pp. 12407–12 417, 2012.

[8] P. Ghamisi, M. S. Couceiro, F. M. Martins, and J. A. Benediktsson, "Multilevel image segmentation approach for remote sensing images based on fractional-order Darwinian particle swarm optimization," *IEEETrans. Remote Sens. Geosci.*, vol. 52, no. 5, pp. 2382–2394, May 2014.

[9] P. Ghamisi,M. Couceiro, M. Fauvel, and J. A. Benediktsson, "Integration of segmentation techniques for classification of hyperspectral images, "*IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 1, pp. 342–346, Jan. 2014.

[10] P. Ghamisi, M. S. Couceiro, and J. A. Benediktsson, "Classification of hyperspectral images with binary fractional order darwinian PSO and random forests," *Proc. SPIE*, vol. 8892, pp. 88 920S–88 920S-8, 2013.