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An Unsupervised Learning of Hyperspectral Images using Fuzzy C-means (FCM) Clustering Method with Glowworm Swarm Optimization (GSO)

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Abstract

The unsupervised learning method is one of the formidable operations in Hyper-Spectral Image (HSI) processing. Fuzzy C-Means (FCM) clustering is an optimistic and strategic method for selecting the unsupervised bands. There are some limits and standards in fuzzy clustering technique. The Glowworm Swarm Optimization (GSO) is proposed with combining fuzzy clustering and GSO. The GSO is introduced to enhance the performance of fuzzy clustering to optimize the characteristics of hyperspectral images. The main objective of the proposed method is to improve the accuracy of the hyperspectral datasets and to achieve it through better computational time. The experimental results are achieved through MATLAB toolbox and the proposed method has the capability to perform with the high quality hyperspectral image classification. Copyright © VBRI Press.

Introduction

This paper, a new unsupervised learning algorithm for Fuzzy C-means (FCM) clustering based Glowworm Swarm Optimization (GSO) has been proposed for Hyper-Spectral Images (HSIs) in satellite remote sensing environment. HSI is ordinarily characterized as a spectral detecting strategy which takes many adjoining narrow waveband images in the noticeable and infrared areas of the electromagnetic range. The image pixels shape in spectral vectors which illustrate to the spectral feature of the materials in the view. Thus, the method has been applied for the most part for material recognition and differentiation intentions (PWT Yuen and M Richardson 2010). HSI permit to describe the objects of interest (land cover classes) with extraordinary accuracy and to hold inventories stay up with the latest technique. Enhancements in spectral resolution have called for propels in signal processing and victimization algorithms (Gustavo Camps-Valls *et al.* 2014). Ensemble based Support Vector Machine (EbSVM) algorithm is an excellent technique which splits the majority classes into different groups with small sizes and also solve the optimization problem. Its construct a new classifier by separately combining the minority classes to each group also (C. Rajinikanth and S. Abraham Lincon 2018). In hyperspectral remote sensing whole spectrum is gained at each point, in this way, needs no earlier information of the sample. Post-processing of the datasets gives all the conceivable data in regards to the sample. For classification and segmentation, hyperspectral remote sensing gives definite data about spectral-spatial models. Hyperspectral remote sensing is economically efficient and gives a non-destructive sampling (Antonio Plaza *et al.* 2009). The SS-SAbC algorithm is more appropriate for training the unlabelled samples for complex dataset in HSIs. Moreover the training dataset is enhanced by adding the similar samples to individual classes (C. Rajinikanth and S. Abraham Lincon 2018).

Hyperspectral Remote Sensing (HRS)

Hyperspectral remote sensing from aerial and satellite frameworks have been used as an information hotspot for various remote sensing applications in the course of recent decades. Hyperspectral imaging is a broadly acknowledged innovation and rapidly moving into the standard of remote sensing research analysis. Here, hyperspectral implies spectra having a substantial number of narrow conterminously divided spectral bands.

Unsupervised Learning (UL)

The unsupervised learning identifies the structure or the characteristics of the input data. Unsupervised learning, each one of the perceptions is thought to be caused by latent factors, that is, the perceptions are presumed to be toward the finish of the causal chain. Instances of supervised learning and unsupervised learning shown in **Fig. 1**.

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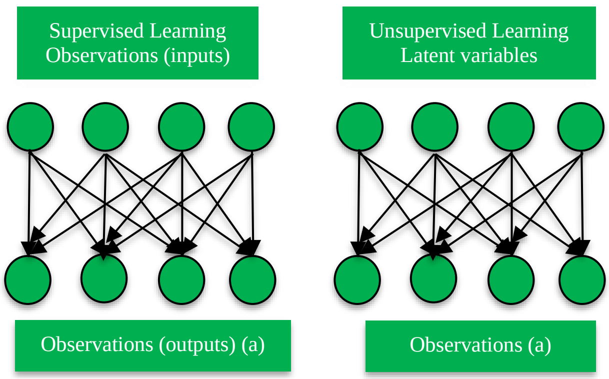


Fig. 1. Instances of Supervised and Unsupervised Learning.

Fuzzy logic

FCM algorithm clusters *N* vectors into *C* fuzzy clusters. Then it obtains *C* centres for the fuzzy clusters to minimize an objective function. The objective function is defined as,

$$\min J = \sum_{i=1}^{C} J_i = \sum_{i=1}^{C} \sum_{i=1}^{N} u_{ij}^{m} d_{ij}^{2} \tag{1}$$

$$u_{ij} = \left\{ u_{ij} \in [0,1] \middle| \sum_{i=1}^{C} u_{ij} = 1 \right\} \tag{2}$$

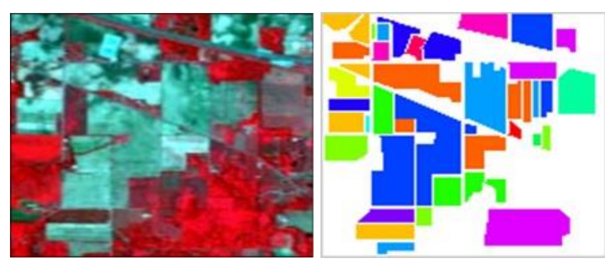
For band determination, *N* is the quantity of total groups and *C* is the quantity of chosen groups. u_{ij} is characterized as move equation (2) here which signifies the fuzzy membership of the j^{th} band comparing to i^{th} cluster. dij = ||ci − xj|| is the Euclidean distance between i^{th} cluster and j^{th} band. The parameter *m* is a fuzzy example that fulfils m ∈ (1, ∞). For limiting equation (1), the Lagrange multiplier technique is received. The fuzzy membership and the update of the iteration conditions of cluster centres can be found as, (Mingyang Zhang, Jingjing Ma, and Maoguo Gong 2017).

Glowworm Swarm Optimization (GSO)

The Glowworm Swarm Optimization (GSO) is a swarm intelligence optimization algorithm created in view of the conduct of glowworms (otherwise called fireflies or lightning bugs). The conduct standard of glowworms which is utilized for this algorithm is the evident ability of the glowworms to convert the volume of the luciferin discharge and along these seem to glow at various powers. The GSO algorithm makes the operators glow at intensities generally corresponding to the function value being improved. It is accepted that glowworms of more splendid intensities attract glowworms which have less intensity. This feature of the algorithm enables it to be utilized to distinguish different pinnacles of a multi-modal capacity and makes in part of Evolutionary multi-modal enhancement algorithms group.

Datasets

In this paper, the following benchmark images of Indian Pine, Pavia University, Salinas Complete and Salinas-A hyperspectral datasets have been considered for proposed classification experiments. The Indian Pines and Salinas-A datasets are captured by AVIRIS sensor with 224 spectral reflectance. The Indian pines wavelength varies from 0.4 to 2.5 × 10^{-6} meters, the pixel range of 145 × 145 and 20m in spatial resolution (C. Rajinikanth and S. Abraham Lincon 2018). There are 16 classes with 10,366 pixels need to be classified. **Fig. 2** shows false color composition and ground truth map of Indian Pines dataset. The Pavia University dataset spectral band varies from 0.43 µm to 0.83 µm, the pixel value of 610× 610 with 103 and 1.3m in spatial resolution. There are nine classes with 42,776 pixels need to be classified. **Fig. 3** shows false color composition and ground truth reference map of Pavia University dataset. The Salinas-A has a pixel value of 86× 83 with six classes and total pixels 6,966 need to be classified. **Fig. 4** shows the false color composition and ground truth reference map of Salinas-A dataset (C. Rajinikanth and S. Abraham Lincon 2018).

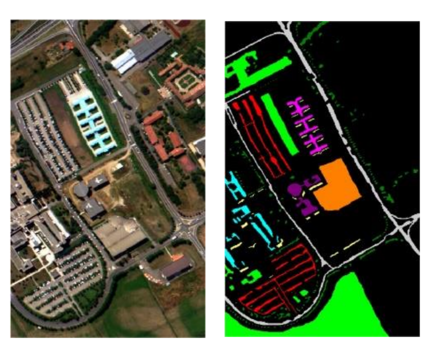


(a) (b)

(c)

Corn-no till	Grass/trees
Corn-min till	Grass/pasture-mowed
Corn	Hay/windrowed
Soybean-no till	Oats
Soybean-min till	Wheat
Soybeans-clean	Woods
Alfalfa	Buildings/Grass/Trees-/Drives
Grass/pasture	Stone/Steel/Towers

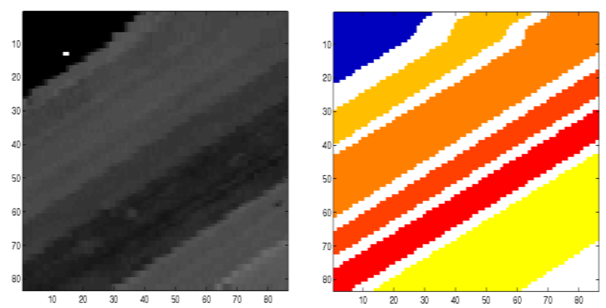
Fig. 2. Dataset of Indian Pines (a) Sample band image (b) Ground truth image and (c) Colour code.



Asphanlt
Meadows
Gravel
Trees
Metal sheets
Bare soil
Bitumen
Bricks
Shadows

(a) (b) (c)

Fig. 3. Dataset of Pavia University (a) Sample band image (b) Ground truth image and (c) Colour code.



(b) (b)

	Brocoli_green_weeds_1
	Corn_senesced_green_weeds
	Lettuce_romaine_4wk
	Lettuce_romaine_5wk
	Lettuce_romaine_6wk
	Lettuce_romaine_7wk

(c)

Fig. 4. Dataset of Salinas A (a) Sample band image (b) Ground truth image and (c) Colour code.

Methodology

Optimization of Fuzzy Clustering with GSO

- Iteration level: 10
- Maximum Iteration = 20
- Clustering points differ from each datasets.

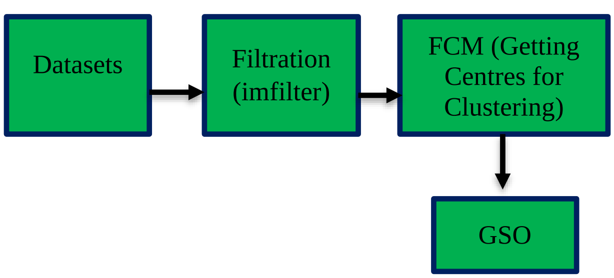


Fig. 5. The process of FCM with GSO.

Filtration

The filtration technique used in this process is imfilter, it is a multidimensional filter and it is one of the image processing toolbox in MATLAB. B = imfilter (A, H) filters. Where, A is the multidimensional array and H is the multidimensional filter. The array A can be logical or a non-sparse numeric array of any class and dimension of each dataset. The result B has the same size and class as A. Each element of the output B is computed using double-precision floating point. If A is an integer or logical array, then output elements that exceed the range of the integer type are truncated, and fractional values are rounded.

Results

The hyperspectral image datasets used for this proposed method is Indian Pines, Pavia University and Salinas A scene. The accuracy and the computational time of each class of the datasets are calculated and obtained. The Accuracy can be calculated by

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{3}$$

where, "TN" is true negative, TP is true positive, FN is false negative and FP is false positive.

By using the FCM-GSO method the accuracy of the Indian Pines datasets with 16 classes is achieved 100% and the computational time to achieve the optimization is 1.5391 sec. Then the accuracy of the Pavia University with 9 classes is achieved 100% with the computational time is 5.8641 sec. Finally the accuracy of the Salinas-A with six classes is also achieved 100% with the computational time is 1.3796 sec are listed in **Table 1** and **Table 2** and corresponding output responses are depicted in **Fig. 6** and **Fig. 7**.

Table 1. Comparison of Computational Time (S) (Mingyang Zhang, Jingjing Ma, and Maoguo Gong 2014).
*NI- Not Identified

Method	Indian Pines	Pavia University	Salinas-A
PSO-FCM	33.39	17.56	NI
FCM	23.03	80.72	NI
CM	6.24	26.91	NI
FCM-GSO	1.5391	5.8641	1.3796

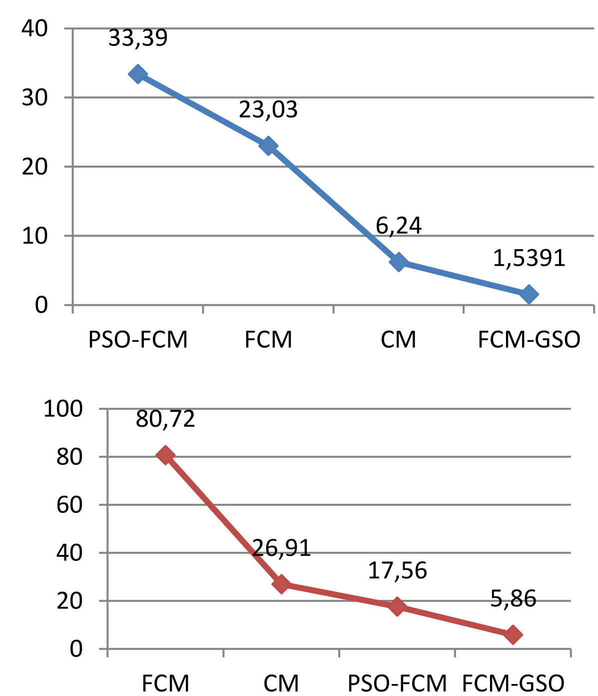


Fig. 6. Representation of Indian Pines and Pavia University Computational Time.

The above **Fig. 6** representing the computational time of the proposed method with the other methods and has achieved less computational time for each datasets compared with others.

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Table. 2. Comparison of Accuracy.

Method	Indian Pines	Pavia University	Salinas-A
GA-SVM	93%	92%	-
PSO	74.55	87.38	-
GSA	74.03	87.97	-
FCM-GSO	100%	100%	100%

*NI- Not Identified

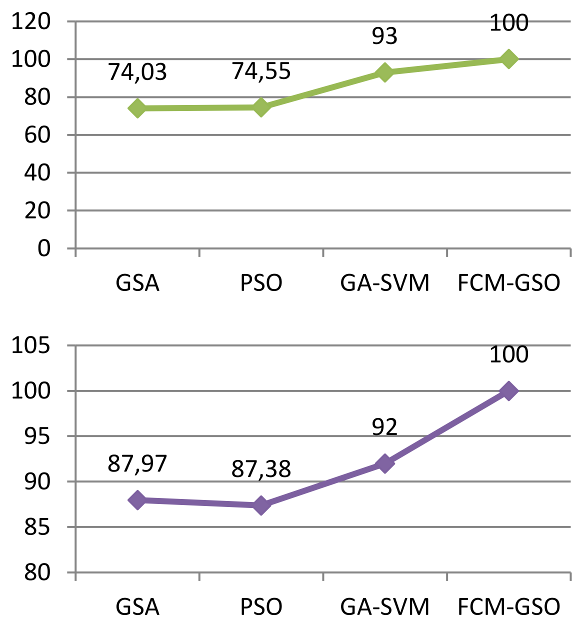

Fig. 7. Representation of Comparing Indian and Pavia University Accuracy.

For both the comparison tables the Indian pines and Pavia University datasets are only gathered and compared for achieving the better result, but the Salinas-A dataset is not compared with other methods because, Salinas-A is not classified with the comparison methods.

By using the proposed Fuzzy C-means Clustering Method with Glowworm Swarm Optimization FCM-GSO method the selected datasets are executed using MATLAB program and the screenshot of each dataset executed by using MATLAB is shown respectively. From the above results the proposed FCM-GSO method is better in all the cases compared with existing methods performed with considered datasets.

Conclusion

The unsupervised learning of hyperspectral images with the proposed FCM-GSO method is used to optimize the hyperspectral image datasets like Indiana Pines, Pavia University and Salinas-A. Each of the datasets has corresponding sample classes with spectral bands and pixel resolution range. The objective of the proposed method is optimized and achieved maximum accuracy with better computational time.

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