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ORIGINAL RESEARCH

Band Selection in Hyperspectral Image with Chaotic Binary MOCLONAL Algorithm

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Abstract

Hyperspectral image comprise of a three dimensional image cube. Two dimension represents the regular image collected on a specific band of frequency. There are hundreds of such correlated bands present in this three dimensional cube. To effectively process and extract significant information from the hyper-spectral image there is a need to eliminate some of the bands which carry repetitive information, sometimes noisy in nature. In IEEE iSES 2021 symposium, a binary multi-objective CLONAL algorithm is reported by the same author to address the band selection problem. In this paper, a modified version of the same algorithm is introduced by considering chaotic sequence based initialization instead of the random number based initialization. Entropy and Pearson correlation are used as the fitness function for multi-objective optimization. Simulation have been performed on hyperspectral images of Pavia University, Kennedy Space Centre. On the obtained band reduced images image segmentation is carried out using K-modes clustering. Comparison is carried out with the results obtained with random number based same algorithm, binary social spider algorithm, NSGA-II algorithm and principal component algorithm.

Keywords Hyperspectral image · Band selection · Multi-objective optimization · Chaotic sequence · CLONAL algorithm

Introduction

Hyperspectral images are captured by the hyperspectral sensors example NASA's Airborne Visible/Infrared Imaging Spectrometer (AVIRIS). These images are captured over continuous ranges of wavelengths. Each image comprise of 100–200 bands and possess high volume of information for analysis. They find potential applications in fire detection inside forest, glacier detection, water detection, landscape monitoring. The challenge is to effectively process the 3D image cube and extract meaningful information [1, 2]. Band reduction in hyperspectral imaging is a problem to remove/filter out the undesired bands (those bands which mostly contain similar information) and keep smaller number of bands which can easily be processed [3, 4].

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In last decade several remote sensing and machine learning researchers have reported many statistical techniques, neural networks based approaches, deep learning based approaches, nature-inspired optimization techniques, multi-objective optimization techniques to find out potential solutions for effective band reduction. The statistical approaches include use of Principal Component Analysis (PCA) [5], noise adjusted principal components [6], kernel PCA [7], nonlinear PCA [8], graph-regularized fast and robust PCA [9], independent component analysis [10, 11], linear discriminant analysis [12, 13], Boltzmann entropy [14]. The real time hardware implementation of PCA based band reduction technique on FPGA is reported in [15].

Several neural networks and deep learning based approaches have been employed for band reduction in hyper-spectral images: Deep feature extraction based on convolutional neural networks (CNN) [16], Attention-based CNN [17] which use CNN along with anomaly detection technique to select effective bands, a band-adaptive spectral-spatial feature learning neural network (BASS net) [18], BS-Nets framework [19], 3-D deep neural network with adaptive band selection mechanism [20], auto encoder for band reduction and CNN for classification [21], cascaded two layers Recurrent Neural Network (RNN) for band reduction [22], attention-based bidirectional long short-term memory network (LSTM) [23].

The nature-inspired meta-heuristics are popular for solving multi-modal optimization problem. Several researchers have formulated the band selection in hyper-spectral image as an optimization problem. Recently Zhao et al. [24] proposed a spectral-spatial genetic algorithm (GA) for effective band selection based on unsupervised learning. The GA has been used along with Support Vector Machine [25], autoencoders [26] and other neural networks for efficient band selection. A modified form of GA using Levy-Flight is employed for band reduction in [27]. The particle swarm optimization (PSO) another popular swarm intelligence based algorithm is also used for band reduction [28, 29]. Zhang et al. [30] combined PSO with Fuzzy Clustering for unsupervised band selection. Other popular nature inspired algorithms employed are: ant colony optimization [31, 32], grey wolf optimizer [33], social spider optimization [34], artificial bee colony algorithm [35], whale optimization [36].

The multi-objective optimization is most of the time a preferred candidate than single objective optimization as it provides the end-user flexibility to select the required solution among a set of solution (Pareto Optimal Set). In recent past multi-objective artificial bee colony [37], multi-objective immune algorithm [38] have been employed for band reduction. The problems which use simultaneously more than three contradictory objectives to optimize are popularly known as the many-objective optimization problem. Prof. Kalyanmoy Deb reported a many objective genetic algorithm popularly known as Non-dominate Sorted Genetic Algorithm (NSGA-III) [39]. In Gupta and Nanda [40] reported a binary version of NSGA-III for effective band selection.

The evolutionary multi-tasking algorithms are introduced by Gupta et al. [41, 42] in which one evolutionary optimization algorithm can able to simultaneously optimize two or more different function by effectively transferring/exchanging the good solutions. Recently Shi et al. [43] used the evolutionary multi-tasking optimization for hyperspectral band selection in semi-supervised manner.

CLONAL algorithm [44] is a nature inspired algorithm based on the principle of operation of biological immune system. The immune cells of a human body provide protection against outside entities like bacteria, virus (termed as antigens). The algorithm imitates the behavior of immune cells. Book by Castro et al. [45], Dasgupta [46] describe the principle of operation and advancements in CLONAL algorithm. Nanda et. al. used CLONAL algorithm for complex Haammerstein system identification [47]. Yin et al. [48] reported a band selection algorithm based on single objective immune clonal strategy.

Inspired by the recent trend of research work in the band selection problem the author recently reported a binary multi-objective CLONAL algorithm in [49]. This manuscript is an extended version of the paper [49]. The key contributions of this paper are:

- Band selection in hyper-spectral images is dealt as a two contradictory-objectives simultaneous optimization problem.
- Introduced a Chaotic sequence based binary number generation for multi-objective CLONAL algorithm.
- Simulation is carried out on two benchmark hyper-spectral images of Pavia University, Kennedy Space Centre.
- Comparative results are analyzed with same binary multi-objective CLONAL algorithm with random number initialization [49], Principal Component Analysis (PCA) , Binary Social Spider Optimization Algorithm (BSSO) [34], Non-dominated Sorted Genetic Algorithm (NSGA-II) [50].

The reminder of this paper is outlined as follows. The following section begins with backgrounds of Clonal selection principle, CLONAL algorithm, band selection problem in hyperspectral image. Proposed chaotic binary multi-objective CLONAL algorithm for band selection is reported in the subsequent. The simulation platform, comparative algorithms, images used for analysis and obtained results are given in "Simulation and Result Discussions". The nexy section concludes the important findings of the paper.

Backgrounds

CLONAL Selection Principle

The CLONAL selection principle is an integral part of immunology [46]. Whenever a human body is invaded by an antigen (outside elements like bacteria, viruses) the immune system responds to it as shown in Fig. 1. The immune system comprise of several antibodies (human body immune cells which protect it from antigen). Here the structure of antigen matches to a portion of antibody y. In order to prevent from further attack by the antigen the antibody y is selected and allowed to proliferate. Here clones of antibody y is produced several times. Then these cloned antibodies undergo hyper-mutation (change in characteristics to deal with new environments). They are then segregated into two categories : Memory cells and Plasma cells. The memory

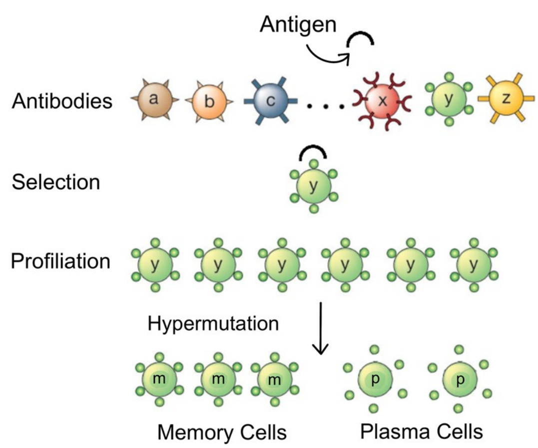

Fig. 1 Schematic diagram of CLONAL selection principle of immunology for antigen detection and response

cells have a longer life span, thus in future when the same antigen attack it will be allowed to clone. The Plasma cell immediately capture the antigen and try to destroy it. This is the overall principle of human body protection against any disease.

CLONAL Selection Algorithm

The CLONAL selection algorithm reported by Castro and Zuben [44] has received more than 3185 citations till date as per the Google Scholar reports which justifies the popularity of the algorithm. A pseudo code of the algorithm is included here in Algorithm 1 for easier understanding.

Band Selection in Hyperspectral Images as a Multi-objective Problem

In recently reported article by the author [49] the selection of optimal number of bands in a Hyperspectral Image is formulated as a multi-objective optimization problem. A multi-objective optimization problem is mathematically represented as

$$F\left(\vec{z}\right) = \left[f_1(\vec{z}), f_2(\vec{z}), \dots f_k(\vec{z})\right] \quad (1)$$

where $F = \left[f_1, f_1, \dots, f_k\right]$ represents k number of fitness functions to be optimized simultaneously. The functions should be contradictory in nature. Simpler way if one function is increasing other one should be decreasing in nature. In [49] two statistical contradictory functions are taken in order to achieve maximum non-similar information among bands (noisy as well as similar information content bands to be rejected).

Proposed Chaotic Binary Multi-objective CLONAL Algorithm for Band Selection

The flowchart of the proposed chaotic binary multi-objective CLONAL algorithm for effective band selection is shown in Fig. 2. The detailed steps are discussed in the following subsections.

Chaotic Sequence Generator

Chaotic sequence generator used in nature inspired optimization algorithms at times provide better exploration

Algorithm 1 CLONAL selection algorithm for optimization

Require: Function for optimization $f(z)$, Given range $\forall z \in [Rmin, Rmax]$
Ensure: Optimized function value in the given input range

```
Initialize : immune cell population size N ⇐ N_max, Iteration G ⇐ G_max
Initialize cell population C = [c_1, c_2, ... c_i ..., c_N], ∀c_i ∈ [Rmin, Rmax]
while G ≠ 0 do
    for i = 1 to N do
        Calculate fitness of each immune cell: f(c_i)
        i ⇐ i + 1
    end for
    Perform : Sorting and select best fit immune cells
    Clone : best fit immune cells
    for i = 1 to N do
        Perform : Hypermutation on each cloned immune cells
        i ⇐ i + 1
    end for
    Select best immune cells for next generation
    G ⇐ G − 1
end while
```

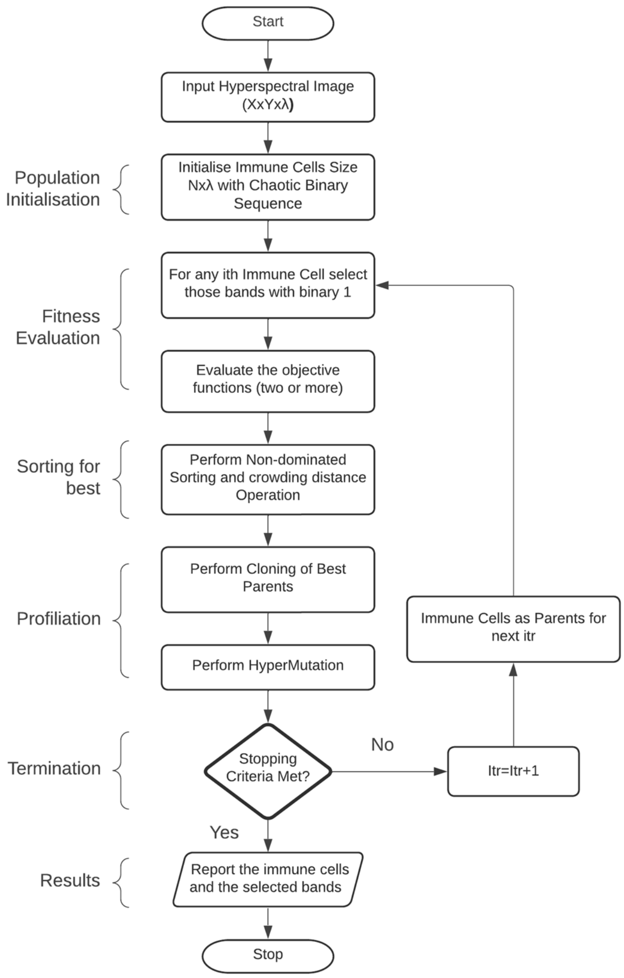

Fig. 2 Flowchart of proposed Chaotic binary MOCLONAL algorithm for band selection in hyperspectral imaging

of search space compared to random number generators. Based on chaotic sequence use single objective optimization algorithms are Fast CLONAL algorithm [51], Social Spider Optimization algorithm [52], Sailfish Optimization algorithm [53]. The logistic map is taken here to generate Chaotic number in range [0, 1]. The equation is given by

$$T_{G+1} = a \times T_G \times (1 - T_G) \tag{2}$$

where T_{G+1} is the Chaotic number value at $(G+1)$th generation, a is a parameter whose value is taken as 4. The T_0 initial value is taken as 0.4.

Immune Cells Population Initialization

The population of immune cells are initialized as

$$C_{N\times\lambda} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ . \\ . \\ . \\ c_N \end{bmatrix} = \begin{bmatrix} 100111....0 \\ 011011....1 \\ 001101....1 \\ .... \\ .... \\ .... \\ 111010....0 \end{bmatrix}_{N\times\lambda} \tag{3}$$

where N is the number of immune cells. Each immune cell represent a solution of this problem and is given by λ size of 1/0 sequence. This 1/0 sequence is taken with Chaotic numbers. Digit 1 reveals band is chosen and 0 reveals band is rejected.

Fitness Functions for Multi-objective Optimization

The spectral entropy H_i^b and Pearson correlation coefficient $R_{i,j}^N$ defined in [49] are used as fitness functions for optimization.

Non-Dominated Sorting and Crowding Distance Operator

The non-dominated sorting is performed to determine the best fit solutions based on convergence. The aim is to bring as many solutions to rank 1. The crowding distance operator take care of the diversity among the solutions. Both these tasks are carried out following the procedure of them given in NSGA-II algorithm [50].

Cloning

The best fit solutions (Rank 1) obtained from 3.4 are allowed to undergo cloning operation following the Algorithm 1 of [49].

Table 1 Hyperspectral images used for analysis

Parameters	Pavia University	Kennedy Space Centre
Number of spectral bands	103	176
Pixels in each band	1096 × 715	512 × 614
Number of classes	9	12
Geometric resolution	1.3 m	18 m
Wavelength range (μm)	0.43–0.86	0.4–2.5

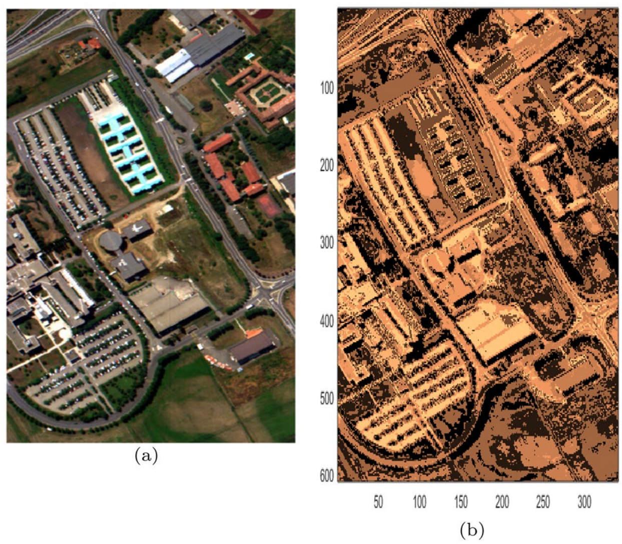

Fig. 3 Hyperspectral image analysis of Pavia University **a** true colour image, **b** segmented image using K-modes clustering after band reduction using proposed Chaotic binary MOCLONAL algorithm

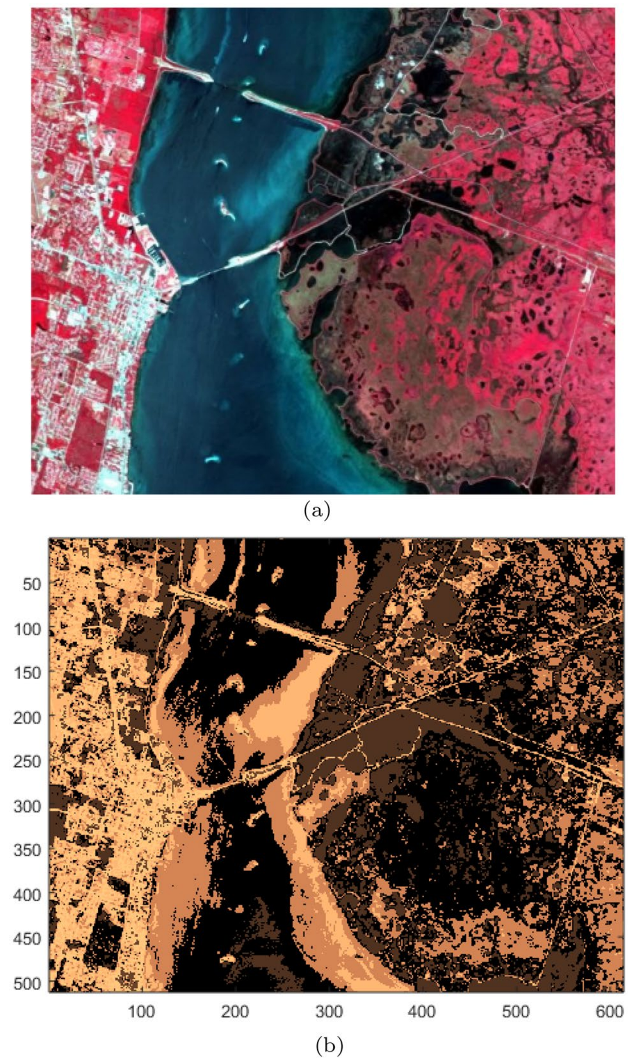

Fig. 4 Hyperspectral image analysis of Kennedy Space Centre **a** true image, **b** segmented image using K-modes clustering after band reduction using proposed Chaotic binary MOCLONAL algorithm

Hyper-mutation

In the cloned solutions diversity is maintained by incorporating hyper-mutation operation. It is carried out using the Algorithm 2 of [49].

Termination Condition

The algorithm is allowed to run for fixed number of iterations. After the convergence is achieved the best immune cell which represent the λ bands is reported.

Simulation and Result Discussions

The simulation work of the proposed algorithm is carried out in a HP LAPTOP with 8GB RAM, intel Core-i7 processor with 2.3 GHz frequency. The other algorithms taken for comparison are: binary multi-objective CLONAL algorithm with random number initialization [49], Principal Component Analysis (PCA) , Binary Social Spider Optimization Algorithm (BSSO) [34], Non-dominated Sorted Genetic Algorithm (NSGA-II) [50]. In all the four nature inspired algorithms the population size is kept 50, the generation number is taken as 10. Hyper mutation rate is fixed at 0.4. The details of the Hyperspectral images used for analysis is included in Table 1.

The true colour hyperspectral image of Pavia University and Kennedy Space Center are given in Figs. 3a and 4a respectively. The segmented image using K-modes clustering after band reduction with proposed MOCLONAL (Chaotic) is shown for Pavia University and Kennedy Space Center in Figs. 3b and 4b. The number of retained bands, run time and accuracy of clustering (with K-modes algorithm) for both Pavia University and Kennedy Space Center are reported in Tables 2 and 3 respectively. The better results are highlighted in bold letters. From both the tables it is observed that the MOCLONAL algorithm has lower run time than NSGAII and Social Spider Algorithm. The number of bands finally selected is also lower in the proposed algorithm compared to the other four algorithms. The final selected bands by each algorithm for Pavia University is reported in Table 4 and for Kennedy Space Centre is given in Table 5. Close observation in both these tables reveal that

Table 2 Comparative analysis of performance on band reduction of Pavia University hyperspectral image

Performance parameters	PCA	NSGA-II	BSSO	MO-CLONAL (Random)	MO-CLONAL (Chaotic)
Retained bands	30	25	47	24	**23**
Run time	34.9900	38.1820	39.8724	30.3706	**28.7502**
Accuracy of clustering	64.25%	76.63%	75.36%	79.87%	**81.52**%

Bold letters represent the best results achieved

Table 3 Comparative analysis of performance on band reduction of Kennedy Space Centre hyperspectral image

Performance parameters	PCA	NSGA-II	BSSO	MO-CLONAL (Random)	MO-CLONAL (Chaotic)
Retained bands	75	64	62	57	**55**
Run time	75.2520	70.1140	77.2624	65.0028	**57.1045**

Bold letters represent the best results achieved

Table 4 Selected bands by proposed MOCLONAL(Chaotic) along with comparative algorithms in Pavia University

Algorithm	Bands selected
MOCLONAL (Chaotic)	[2 5 8 12 15 18 24 30 32 39 43 47 53 55 62 63 64 70 74 77 84 86 97]
MO-CLONAL (Random)	[5 7 10 12 15 17 18 22 28 29 32 37 41 45 51 56 62 70 76 78 84 85 87 90]
BSSO	[1 2 3 6 8 11 13 17 19 24 27 29 34 37 39 50 52 60 64 66 68 72 73 74 75 76 77 83 84 87 94 96]
NSGA-II	[2 5 8 12 15 18 24 25 30 32 39 43 47 53 55 62 63 64 70 74 77 84 86 97 101]
PCA	[1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30]

Table 5 Selected bands by proposed MOCLONAL(Chaotic) along with comparative algorithms in Kennedy Space Centre

Algorithm	Bands selected
MOCLONAL (Chaotic)	[1 3 5 7 10 12 14 17 19 22 27 28 32 36 39 43 45 49 51 53 57 58 60 62 67 70 72 73 78 79 80 83 89 90 91 97 102 107 111 113 117 121 125 129 132 135 138 142 144 147 151 158 162 168 170 175]
MO-CLONAL (Random)	[1 3 5 7 9 12 14 17 19 22 27 28 32 35 39 43 45 49 51 53 57 58 60 62 67 70 72 73 78 79 80 83 89 90 91 97 100 102 107 111 113 117 121 125 129 132 135 137 138 142 144 147 151 158 162 167 170]
BSSO	[1 3 5 7 11 15 22 24 28 32 33 36 39 45 47 49 51 53 60 73 78 80 86 93 99 100 102 103 105 107 108 115 118 120 121 124 127 129 132 133 134 136 138 141 143 146 147 150 151 153 157 161 164 167 169 170 174]
NSGA-II	[1 2 4 5 7 8 9 11 12 13 14 16 22 24 26 27 28 29 31 47 50 51 52 55 58 60 61 62 66 69 70 71 72 73 77 79 80 82 83 84 87 88 94 95 97 101 107 111 116 117 119 122 124 127 132 133 138 139 143 146 148 158 162 168 175]
PCA	[1 3 5 7 11 15 17 22 24 26 28 32 33 36 39 45 47 49 51 53 57 60 73 78 80 83 86 93 97 99 100 102 103 105 107 108 115 118 120 121 124 127 129 132 133 134 136 138 141 143 146 147 150 151 153 157 159 161 164 167 169 170 173 175]

most of the bands selected by these algorithms are disjoint (not-continuous) in nature.

Conclusion

The CLONAL algorithm is popular due to its faster convergence. In this manuscript a chaotic binary multi-objective CLONAL algorithm is introduced for band selection in hyperspectral image. Due to the involvement of chaotic sequence the algorithm performance is better compare to the random number sequence. Simulation on Pavia University and Kennedy Space Center image reveal the effective performance of the proposed algorithm in the form of lower number of band retention, higher clustering accuracy and lower computational time compared to the four already reported algorithms. The author is working on use of proposed Binary MOCLONAL algorithm to solve real-life multi-objective problems.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

Human participants or animals rights This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

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