Binary Cuckoo Search Algorithm for Band Selection in Hyperspectral Image Classification

Seyyid Ahmed Medjahed, Member IAENG, Tamazouzt Ait Saadi, Abdelkader Benyettou, and Mohammed Ouali

Abstract— Spectral band selection has been a very active and important field of research in hyperspectral image classification. The hyperspectral images contain redundant measurements and irrelevant information which reduce significantly the classification accuracy rate. In this paper, we propose a new framework for band selection problem based on Binary Cuckoo Search. We cast the problem of band selection as a combinatorial optimization problem and we use a binary version of Cuckoo Search algorithm which is a new metaheuristic algorithm more efficient than practical swarm optimization and genetic algorithms. The experiments were applied on three widely used benchmark hyperspectral data sets. The proposed approach was used under the k-nearest neighbor classifier and compared with several feature selection algorithms defined in the literature. The results show that the proposed approach provides a high classification accuracy rate in comparison to other approaches by using a few samples for training and a small number of bands.

Index Terms— Spectral band selection, hyperspectral image classification, binary cuckoo search, optimization

I. INTRODUCTION

RECENTLY, hyperspectral image classification has been very interesting field of research in many applications [1-3]. It consists to classify each pixel in a specific label. The hyperspectral images are composed of hundreds of bands with very high resolution taken under different frequencies. The National Aeronautics and Space Administration (NASA) Jet Propulsion Laboratory is the first that has used the hyperspectral images and builds the Airborne Visible-Infrared Imaging Spectrometer (AVIRIS). The AVIRIS can records hyperspectral image using more than 200 spectral bands with very high resolution and high-dimensional image data [4-5].

In the classification of hyperspectral images, several problems should be taken on consideration such as: the quality of bands and the high number of spectral channels. However, the application of the band/feature selection approach can significantly decreases the computational time and space dimension. Also, the selection of relevant bands extremely improves the classification accuracy rate. The aims of the band selection are to find the most important information from a given set of band by removing the irrelevant and the highly correlated bands.

Feature selection approaches are classified into two general groups: Filter and Wrapper approaches. The first defined a heuristic scoring to measure the quality of features without using classifiers. The filter approaches are very fast and more practical on high-dimension data but they ignore the feature dependencies. The Wrapper approaches are based on the use of classifiers. These approaches are very slow because they must repeatedly call the classifier algorithm, but, they reach a high classification accuracy rate compared to filter approaches [6-8].

In this paper, we model the band selection problem as a combinatorial optimization problem in which a set of features that leads to the best feature space separability is then employed to map the original data to a new one. To solve the combinatorial problem, we use a new version of Cuckoo Search (CS) algorithm which is a one of recently nature-inspired metaheuristic algorithms developed in 2009 by Xin-She Yang of Cambridge University and Suach Deb of C. V. Raman College of Engineering [9]. Recent studies show that CS algorithm is potentially far more efficient than practical swarm optimization and genetic algorithms [10]. The effectiveness of the proposed approach is demonstrated on three hyperspectral image data sets: Indian Pines Scene, Salinas Scene and Pavia University Scene. We compared the obtained results with several feature selection approaches and several classifiers without feature selection. The remainder of the paper is organized as follows: Section II describes and presents the proposed approach. In Section III, we discuss the experimental results. In Section IV, conclusions are drawn with some perspectives.

II. THE PROPOSED BAND SELECTION APPROACH

The purpose of the proposed approach is to reformatulate the band selection problem as a combinatorial optimization problem defined as follows:

Let \( b = \{b_1, b_2, ..., b_d\} \) the band set of hyperspectral image dataset \( D \) with \( d \) features.

Let \( x = [x_1, x_2, ..., x_d] \) a binary vector with \( x_i \in \{0,1\} \). We define the pair \((b_i, x_i)\) with:

\[ x_i = \begin{cases} 0 & \text{if \( b_i \) is not selected} \\ 1 & \text{if \( b_i \) is selected} \end{cases} \]
The proposed binary Cuckoo Search Algorithm for Band Selection

A. The Proposed Binary Cuckoo Search Algorithm for Band Selection

Rodrigues et al. [11] proposed a binary version of Cuckoo Search Algorithm namely BCS (Binary Cuckoo Search) and used it for theft detection in power distribution systems. In this study, we adopt the BCS algorithm for band selection problems in hyperspectral image classification. The algorithm selects the relevant and the smallest subset of bands that decreases the classification error rate. This version is defined as follows:

Input: The hyperspectral image dataset \( D \), number of nests \( m \), number of bands \( d \), number of iterations \( T \).

Output: The subset of selected bands.

\[
\begin{align*}
\text{For each nest } n_i \text{ from } 1 \text{ to } m & \text{ do} \\
& \text{For each band } b_j \text{ from } 1 \text{ to } d \text{ do} \\
& \quad x(i,j) \leftarrow \text{Random}[0,1] \\
& \text{End For} \\
& \text{End For} \\
& f \leftarrow 1 \\
\end{align*}
\]

\[
\begin{align*}
& \text{For each iteration } t \text{ from } 1 \text{ to } T \text{ do} \\
& \quad D \leftarrow \text{hyperspectral image data} \\
& \quad \text{For each nest } n_i \text{ from } 1 \text{ to } m \text{ do} \\
& \quad \quad \text{For each band } b_j \text{ from } 1 \text{ to } d \text{ do} \\
& \quad \quad \quad \text{If } x(i,j) = 0 \text{ then} \\
& \quad \quad \quad \quad D' \leftarrow D - \{\text{the band } j\} \\
& \quad \quad \text{End If} \\
& \quad \text{End For} \\
& \quad \text{End For} \\
& \quad \text{End For} \\
\end{align*}
\]

Split pixels of \( D' \) into: training and testing set
Train the classifier with the training set and evaluate it over testing set
Calculate the classification error rate \( f' \)
If \( f' < f \) then
For each band \( j \) from \( 1 \) to \( d \) do
\[ x(i,j) \leftarrow x(i,j) \]
End For
End If
End For
End For
For each nest \( n_i \) from \( 1 \) to \( m \) do
For each band \( b_j \) from \( 1 \) to \( d \) do
Select the worst nests according to \( \rho \in [0,1] \) and replace them for new solution
End For
End For
For each nest \( n_i \) from \( 1 \) to \( m \) do
For each band \( b_j \) from \( 1 \) to \( d \) do
\[ \text{step} \leftarrow \mu / |y(i,j)| \]
\[ x(i,j) \leftarrow x(i,j) + \text{step} \]
If \( x(i,j) > \sigma \) then
\[ x(i,j) \leftarrow 1 \]
Else
\[ x(i,j) \leftarrow 0 \]
End If
End For
End For

The algorithm starts with a random solution; each nest contains a vector of binary values randomly generated, and the initial value of the objective function is set to \( I \) (classification error rate = \( I \)). In each iteration of the algorithm and for each solution in the nest, the algorithm constructs a new hyperspectral image by removing the bands that have \( x_i = 0 \) (bands which are not selected). A new training and testing sets are constructed and we use a classifier to calculate the classification error rate. In this phase, the algorithm evaluates the objective function and store the best nest. The next step is to select the worst nests by using the probability \( \rho \) and replace them with random nests. The final loop updates the nests by generating a solution via the Manteugna’s algorithm [12]:

\[
\text{step} \leftarrow \frac{\mu}{\sqrt{2 \pi}}
\]

where \( \mu \) and \( \nu \) are generated from normal distribution.

B. The Objective Function

The objective function evaluates candidate subsets and returns a measure of their performance. The objective functions are divided in two classes:

- The first one is used in the filters approaches; it evaluates the subsets of selected features by their information content: distance of classes, information theoretic, statistical dependence, etc.
• The second category is considered for the wrappers approaches. It uses the classifier system to evaluate the selected features.

In this study, we use two objective functions:

**First Objective Function:** Generally, the classification error rate is used as the principal objective function. The problem of feature selection will be to select the subset of features that minimize the error rate. Is defined as follows:

\[
f_j(b) = \frac{\text{Incorrectly Classified Instances}}{\text{Classified Instances}}
\]

(2)

The classification error rate is calculated by using a classifier system under the subset of candidate features.

**Second Objective Function:** We propose to combine two important terms: the balance error rate and the discriminant ability of features. The problem of feature selection consists to select the relevant subset of features which optimize the error rate and well separate the classes in the features:

The balance error rate (BER) is considered as the main criterion in the feature selection problem. It is given by [14]:

\[
BER = \frac{1}{2} \left( \frac{\text{positive instances predicted wrong}}{\text{positive instances}} + \frac{\text{negative instances predicted wrong}}{\text{negative instances}} \right)
\]

The BER is the average of the errors on each class.

The second term is the F-score measure which calculates the discriminant ability of feature. For a feature \( i \), the F-score measure is defined as follows [14]:

\[
F(i) = \frac{\left( \frac{1}{n_i-1} \sum_{k=1}^{n_i} (\bar{x}_k^{(+)} - \bar{x}_i^{(+)} \right)^2 + \left( \frac{1}{n_i-1} \sum_{k=1}^{n_i} (\bar{x}_k^{(-)} - \bar{x}_i^{(-)} \right)^2}{n_i}
\]

where \( \bar{x}_i^{(+)} \) and \( \bar{x}_i^{(-)} \) are the average of the feature \( i \) positive and negative datasets, respectively; \( x_k^{(+)} \) and \( x_k^{(-)} \) are the feature \( i \) of the \( k \) positive instance and negative instance respectively [14].

The F-score defined above is considered for the binary features (two classes). To address the problem of multi-classes, we defined the following equation of F-score for a set of selected features:

\[
FS(b) = \frac{\sum_{i=1}^{d} b_i \cdot F(i)}{\sum_{i=1}^{d} F(i)}
\]

(3)

where \( b \) is a binary vector which defined a feature \( i \) is selected or not (\( b_i=1 \) the feature \( i \) is selected, \( b_i=0 \) the feature \( i \) is not selected).

The equation (3) calculates the ration of F-score for a set of selected features.

The objective function to optimize is the sum of two terms:

\[
f_2(b) = a_{BER} \times BER(b) + a_{FS} \times FS(b)
\]

(4)

Where \( a_{BER} \) and \( a_{FS} \) is the weight coefficients of the BER and F-score term respectively.

### III. EXPERIMENTAL RESULTS AND DISCUSSIONS

#### A. Hyperspectral Image Datasets

The performances analysis of the proposed approach was conducted under three real hyperspectral image datasets widely used in the literature [1-5].

The first hyperspectral image is an airborne data set taken from the ROSIS sensor. This scene contains 113 spectral bands in the spectral range from 0.43 to 0.86 μm with 640×340 pixels taken over the University of Pavia in Italy. The Pavia University Scene contains 9 ground truth classes: Asphalt, Meadows, Gravel, Trees, Painted Metal Sheets, Bare Soil, Bitumen, Self-Bloking Bricks, and Shadows.

The second hyperspectral image used in this study was collected by the AVIRIS sensor. This hyperspectral image was taken over the Indian Pines region in Northwestern Indiana which is a mixed of agricultural and forest area. The size of this scene is 145×145 pixels and it is composited of 220 bands in the wavelength range from 0.4 to 2.5 μm. The Indiana Pines Scene consists of 16 ground truth classes, namely: Alfalfa, Corn-notchill, Corn-mintill, Corn, Grass-pasture, Grass-trees, Grass-pasture-mowed, Haywindrowed, Oats, Soybean-notchill, Soybean-mintill, Soybean-clean, Wheat, Woods, Buildings-Grass-Trees-Drives, and Stone-Steel-Towers.

The last hyperspectral data was acquired over Salinas Valley in Southern California, USA by AVIRIS Sensor. The number of spectral bands is 224 bands over 512×217 pixels. The range of spectral is 0.4 to 2.5 μm. The ground truth of this scene differentiates 16 classes: Broccoli-green-weeds-1, Broccoli-green-weeds-2, Fallow, Fallow-rough plow, Fallow-smooth, Stubble, Celery, Grapes-untrained, Soil-vinyard-develop, Corn-senesced-green-weeds, Lettuce-romaine-4wk, Lettuce-romaine-5wk, Lettuce-romaine-6wk, Lettuce-romaine-7wk, Vineyard-untrained and Vineyard-vertical-trellis.

#### B. Parameters Settings

The parameters of the proposed approach are setting as follows: The number of nests is set to 20. The algorithm stops when the value of objective function is 0, or, when the algorithm reaches the total number of iterations T=100. The classifier used to calculate the objective function in the Binary Cuckoo Search for band selection is the k-nearest neighbour (KNN) algorithm. The KNN algorithm is used with the Euclidean distance and \( k=7 \) (7 nearest neighbours).

For each classifier system, the number of samples used for training and test phases must be determined. In this study, we consider (10%) of pixels for the training and the remaining pixels (90%) are considered for the test and validation. To overcome the problem of overfitting, we propose to use split the 90% of pixels to two sets: test set and validation set. The validation set is used under the final subset of band, and, the test set is used under the BCS algorithm. The table 1 presents the number of pixels considered for training and testing in each hyperspectral images.
C. Experimental Results

In this section, we present the experimental results obtained by the proposed approach. The experimentations are conducted in terms of: overall accuracy (OA) which is the number of correctly classified pixels with respect to the total number of test pixels, average accuracy (AA) and Individual Class Accuracy (ICA). The stability measures are also used.

We compared the proposed approach with five filter feature selection techniques: mRmR, CMIM, JMI, MIFS, Relief, and with the most widely feature selection method used in the literature: GA (Genetic Algorithm for Feature Selection) which is a wrapper technique. To validate the performances our approach, we compared it with tow classifier systems without using feature selection techniques. We consider: the SVM and KNN classifier systems by using all the features.

The table 2 illustrates the results OA, AA and individual class accuracies obtained under the Pavia University Scene hyperspectral image.

Table 2 presents the classifications accuracy rate provided by the proposed approach and other methods. The columns represent the different methods used in the comparison protocol and the last column contains the results of our approach. The rows represent the classes of the hyperspectral images and the two last columns contain respectively the average accuracy and overall accuracy.

We clearly note that in the challenging classification scheme, the proposed approach reaches better results and good performances that the other methods. Furthermore, the proposed approach significantly improves the OA and AA. Compare with SVM, the results are slightly similar in term of AA.

The BCS algorithm is very performance when is used with the objective function $f_2$. The good results are recorded for the objective function $f_2$ with 90,17% of average accuracy and 92,60% of overall accuracy.

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TABLE 4. OA (%), AA (%), INDIVIDUAL CLASS ACCURACIES (%) OBTAINED BY THE PROPOSED APPROACH AND COMPARED WITH DIFFERENT FEATURE SELECTION APPROACHES AND TWO CLASSIFIERS WITHOUT FEATURE SELECTION APPLIED TO THE SALINAS HYPERSONTAL DATA SET BY USING 10% OF SAMPLES AS TRAINING SET.

<table>
<thead>
<tr>
<th>#</th>
<th>Class</th>
<th>Feature Selection Approaches</th>
<th>All the bands</th>
<th>This Study</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>mRmR</td>
<td>cmim</td>
<td>jmi</td>
</tr>
<tr>
<td>1</td>
<td>Brocoli_green_weeds_1</td>
<td>93.97</td>
<td>98.69</td>
<td>97.01</td>
</tr>
<tr>
<td>2</td>
<td>Brocoli_green_weeds_2</td>
<td>95.84</td>
<td>99.56</td>
<td>99.43</td>
</tr>
<tr>
<td>3</td>
<td>Fallow</td>
<td>85.39</td>
<td>98.73</td>
<td>98.48</td>
</tr>
<tr>
<td>4</td>
<td>Fallow_rough_plow</td>
<td>99.73</td>
<td>99.73</td>
<td>99.73</td>
</tr>
<tr>
<td>5</td>
<td>Fallow_smooth</td>
<td>94.91</td>
<td>96.13</td>
<td>95.19</td>
</tr>
<tr>
<td>6</td>
<td>Stable</td>
<td>99.27</td>
<td>99.81</td>
<td>99.84</td>
</tr>
<tr>
<td>7</td>
<td>Celery</td>
<td>95.98</td>
<td>99.44</td>
<td>99.13</td>
</tr>
<tr>
<td>8</td>
<td>Grapes_untrained</td>
<td>76.54</td>
<td>82.54</td>
<td>79.96</td>
</tr>
<tr>
<td>9</td>
<td>Soil_vinyard_develop</td>
<td>97.76</td>
<td>97.92</td>
<td>97.60</td>
</tr>
<tr>
<td>10</td>
<td>Corn_senesced_green_weeds</td>
<td>75.60</td>
<td>91.80</td>
<td>88.37</td>
</tr>
<tr>
<td>11</td>
<td>Lettuce_romaine_4wk</td>
<td>60.94</td>
<td>93.33</td>
<td>93.68</td>
</tr>
<tr>
<td>12</td>
<td>Lettuce_romaine_5wk</td>
<td>86.64</td>
<td>99.74</td>
<td>99.81</td>
</tr>
<tr>
<td>13</td>
<td>Lettuce_romaine_6wk</td>
<td>96.45</td>
<td>98.23</td>
<td>97.54</td>
</tr>
<tr>
<td>14</td>
<td>Lettuce_romaine_7wk</td>
<td>92.41</td>
<td>94.39</td>
<td>94.51</td>
</tr>
<tr>
<td>15</td>
<td>Vineyard_untrained</td>
<td>57.33</td>
<td>60.00</td>
<td>61.99</td>
</tr>
<tr>
<td>16</td>
<td>Vineyard_vertical_trellis</td>
<td>76.42</td>
<td>98.27</td>
<td>97.72</td>
</tr>
</tbody>
</table>

The results obtained by the SVM and KNN by using all the bands are identical to our approach by using the objective function $f_1$ with an advantage in overall accuracy.

The second experiment is conducted in Indian Pines hyperspectral image. The obtained results are described in table 3.

The table 3 shows the OA, AA and individual class accuracies obtained by our approach with regard to other methods. All the experimentations have been made with the same training and test sets. Compare with other methods, our approach provides good results and it can be observed that the others in term of OA. Also, we show that our feature selection approach provides satisfactory results when the objective function $f_2$ is used. SVM by using the entire band provides results closer to our approach.

Note that in the both table 2 and 3, the results of SVM are reported from [13].

Finally, we conduct experiments on Salinas Scene hyperspectral image. The table 4 shows the obtained results.

Table 4 presents a comparison protocol between the results obtained by our approach and the other methods. In all considered classes, the classification accuracy rate obtained by the proposed approach is better than the corresponding result for other methods.

The best results are observed when the objective function $f_2$ is used.

Fig.1. and Fig.2. show the AA and OA obtained by our approach and compared to others methods.

![Fig. 1. Average accuracy bars results of Pavia University, Indian Pines and Salinas scene.](image-url)

(Revised online publication: 18 August 2015)
Fig. 2. Overall accuracy bars results of Pavia University, Indian Pines and Salinas scene.

Fig. 3. The classification maps obtained by the proposed approach for each hyperspectral data set by using the objective function $f_1$.

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In this study, we have used the hyperspectral pixel classification to evaluate the performance of the proposed band selection approach. All the produced classification results are illustrated in the figures Fig.1 and Fig.2. We analyzed the results by using two different schemas: average accuracy bars and overall accuracy bars. The AA and OA bars represent the comparative results for the Pavia University, Indian Pines and Salinas scenes produced by several feature selection methods.

It is clearly observed from figures Fig.1 and Fig.2, that the results provided by the proposed approach dominates all the other approach. Moreover, the average accuracy and overall accuracy bars of the proposed approach with objective function \( f_2 \) and objective function \( f_1 \) are the top positions at the rank of classification performance.

As shown in Fig.2, with regard to the Indian Pines scene, the accuracy obtained by the proposed approach are very good and outperform to other methods, with an advantage to the proposed approach used with the objective function \( f_2 \).

Figure Fig.3. shows the Hyperspectral image visualization results.

The first column of the figure Fig.3. represents the spectral image band number 10 of Pavia University and Indian Pines Scene, and the band number 30 for the Salinas Scene. The second column is the Ground Truth of each hyperspectral image data set. The third column corresponds to the classification map obtained by the proposed approach by using the function \( f_1 \).

The visual results are illustrated on the figure Fig.3. and it shows that for both classification maps of Pavia University and the Salinas Scenes are very satisfactory and very similar to the ground truth.

We clearly remark some dissimilarity on Indian Pines classification map compared to it ground truth; this is explained by the small number of training pixels. The Indian Pines hyperspectral image is 145×145 pixels and classified into 16 categories. We have used 10% of ground truth data as training samples which make the learning phase very difficult. For example, the class “Oats” contains 20 pixels, so the number of pixels used for training this class is 2 pixels.

In all hyperspectral maps, the results generated by the proposed approach are encouraged. This is explained by the fact that the proposed approach takes advantage from the binary cuckoo search algorithm that minimizes the classification error rate and attempts to reach the optimum by choosing the relevant bands.

The effectiveness of a feature selection method can be estimated by computing the stability measure. In other terms, the stability is the robustness measure of the feature selection method by selecting different feature subsets produced on different training sets [15]. Several stability measures have been proposed, in this study, we use the \( S_S \) stability, \( S_H \) stability and Kuncheva stability \( I_C \) which are widely used in the literature. These stability measures are defined as follows:

Given two feature subsets \( s_i \) and \( s_j \), the \( S_S \) stability proposed by Kalousis et al. [15] is given by:

\[
S_S = 1 - \frac{|S_i| + |S_j| - 2|S_i \cap S_j|}{|S_i| + |S_j| - |S_i \cup S_j|}
\]

With \( |.| \) is the cardinality.

Dunne et al. [16] defined the stability as the relative Hamming distance. The \( S_H \) stability is defined as:

\[
S_H = 1 - \frac{|S_i \setminus S_j| + |S_j \setminus S_i|}{n}
\]

The value of \( S_S \) and \( S_H \) are between [0,1].

In [17], Kuncheva define the stability \( I_C \) as the consistency index for two feature subsets:

\[
I_C = \frac{r \frac{k^2}{n}}{k - \frac{k^2}{n}} = \frac{rn - k^2}{k(n - k)}
\]

With \( k = |S_i| = |S_j| \) and \( r = |S_i \cap S_j| \).

The subsets must have the same cardinality; the value of \( I_C \) is between 1 and -1.

The stability measure of more than two subsets is the average of all pairwise.

To measure the stability of our proposed approach, we run the BGWO algorithm with the objective function \( f_2 \) 20 times under 20 different training sets for each hyperspectral image.

The results of stabilities measures are plotted in the following figures.
Figures 4, 5 and 6 show the $S_S$, $S_H$ and Kuncheva stability obtained by our approach for each hyperspectral image. The blue box indicates the upper and the lower quartiles. The small circle represents the median values and the blue line indicates the maximum and the minimum values. The stabilities obtained for each hyperspectral image have values between 0.9 and 1. A value close to 1 means that our proposed approach is very stable and remains unchanged against the different training sets. Also, the proposed approach produces almost the same features subset for different training sets.

Figures 7, 8 and 9 illustrate the Stability versus the mean overall accuracy.
Figures 6, 7 and 8 show the $S_5$, $S_7$ and Kuncheva stability obtained by proposed approach versus the mean overall accuracy for each hyperspectral image.

A robust feature selection approach is an approach that has stability close to 1 and produces a high classification accuracy rate. We clearly show in the figures 6, 7 and 8 that the results obtained by our approach appear in the top of the figures.

Finally, we can say that the proposed approach is very stable and provides the same subsets of features regardless of the training set and produces a high classification accuracy rate.

VI. CONCLUSION

In this paper, a new framework for band selection in hyperspectral image classification has been proposed. The proposed approach is based on the new optimization approach called binary cuckoo search algorithm which is a binary version of cuckoo search algorithm. The problem of band selection has been reformulated as combinatorial problem and the objective function to minimize is the classification error rate. The binary cuckoo search is used to optimize the problem. Very recent studies have shown that the cuckoo search is very efficient than practical swarm optimization and genetic algorithms. Experiments have been carried out on three real hyperspectral image data sets: Pavia University, Indian Pines and Salinas Scene. For the three considered data sets, the analysis of the results shows that the proposed approach provides satisfactory results with regard to other feature selection approaches and classifier systems that used all the feature space.

The proposed approach is more robust and reliable than the other methods when the objective function $f_2$ is used. Although the results obtained by our approach are very good. We also conclude that this approach is suitable for band selection problem with small number of training instances.

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