A New Dimensionality Reduction Algorithm for Hyperspectral Image Using Evolutionary Strategy

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Abstract—Reducing the redundancy of spectral information is an important technique in classification of hyperspectral image. The existing methods are classified into two categories: feature extraction and band selection. Compared with the feature extraction, the band selection method preserves most of the characteristics of the original data without losing valuable details. However, the choice of the effective band remains challenging, especially when considering the computational burden, which makes many enumerative methods infeasible. Recently, immune clonal strategy (ICS) has been applied to solve complex computation problems. The major advantages of algorithms based on ICS are that they are highly paralleled, distributed, adaptive, and self-organizing. Therefore, in this paper, we convert the band selection problem into an optimization issue and propose a new algorithm, ICS-EBS (ICS-based effective band selection), to solve effective band combinations. Then, the selected bands are used in classification of hyperspectral image. We evaluated the proposed algorithm by using two data sets collected from the Washington D.C. Mall and Northwest Tippecanoe County. ICS-EBS was compared against one latest proposed band selection algorithm, Inter-Class Separability Index Algorithm (ICSIA). We also compared the results with those achieved by other stochastic algorithms such as Genetic Algorithm (GA) and Ant Colony Optimization (ACO). The experimental results indicate that our proposed algorithm outperforms ICSIA, GA-EBS, and ACO-EBS for hyperspectral image classification.

Index Terms—Immune Clonal Strategy, Band Selection, Optimization, Classification.

I. INTRODUCTION

Over the past a few years, satellite-equipped imaging spectrometers are successfully used for environmental monitoring and mapping. For example, Santini et al. developed an inversion technique to retrieve water constituent concentrations from hyperspectral data [1]; Mitria and Gitasc employed a combination of very high spatial resolution (QuickBird) and hyperspectral (EO-1 Hyperion) imagery to map post-fire forest regeneration and vegetation recovery on the Mediterranean island of Thasos [2]. The hyperspectral imagery equipment is also used in the biological applications. For example, Stagakis et al. focused on the potential of satellite hyperspectral imagery to monitor vegetation biophysical and biochemical characteristics through narrow-band indices and different viewing angles [3]. The reason of promising applications of using imaging spectrometers is that a hyperspectral image, or an image cube, contains hundreds of bands with fine spectral resolution as well as spatial information [4], [5]. However, the large volume data contained in the image cube causes difficulties in data record, storage, transmission, and processing. Not all bands contribute effectively to many specific tasks, as the contiguous bands are strongly correlated [6], [7]. Therefore, it is important to develop a technique that reduces the redundancy of spectral information without losing valuable details [8]. In real industrial application, the way of choosing the effective band combinations or reducing the redundant hyperspectral data can be used as a helpful guidance for the design of imaging spectrometer. Specifically, only the chosen bands data could be allowed to transmit from a satellite-equipped imaging spectrometer for different application purposes. This will be greatly conducive to system resources saving because of the limitation of the satellite-equipped spectrometer that might not be capable of transmitting large amounts of data.

Two major methods, feature extraction and band selection, are currently used to reduce redundancy in hyperspectral image [9]. The feature extraction method is based on data transformation, and extracts features from the original bands to construct a lower-dimension feature space. Most traditional methods belong to the feature extraction category, such as Fisher’s linear discriminant analysis [10], principal component analysis [11], independent component analysis [12], and wavelet transform [13]. These methods, however, usually change the physical characteristics of each original spectral band. Compared with the feature extraction method, the band selection method chooses the effective combination of the original bands, which contain most of the original data for a specific purpose [5], [14], [15]. Although previous work has proposed many methods trying to solve this problem, the choice of the effective bands for different application purposes remains challenging. In this paper, we focus on the band selection method for dimensionality reduction.

Many computational evolutionary algorithms are now used to solve industrial optimization problems [16]. Sung-Ho et al. designed a new controller with the addition of an observer whose gain was obtained by solving a multi-objective optimization problem through the application of a genetic algorithm [17]. Kit-Yan et al. used particle swarm optimization approach to generate fuzzy nonlinear regression models, which sought address all of the common issues in developing models for manufacturing processes [18]. Joon-
Woo et al. proposed a new approach to solving the efficient-energy coverage problem, which was an important issue when implementing wireless sensor networks, using a novel ant colony optimization algorithm [19]. Recently, the study of artificial immune systems (AIS) has attracted considerable attention, and its immune evolutionary strategy can also be applied to solve complex computation or engineering problems [20]. AIS is considered to be a highly paralleled, distributed, adaptive, and self-organizing system, and has a powerful ability to self-learn, identify, and memorize [21]. In 2000, De Castro proposed a typical immune clonal selection algorithm [22], which is an important branch of AIS. The immune clonal selection algorithm derived from clonal selection theory mainly includes three immune operators: a clone operator, a mutation operator, and a selection operator. The three operators present the mechanisms of affinity maturation, cloning, and memorization [22], [23]. The immune clonal strategy (ICS) provides powerful global search ability. Algorithms based on these immune operators can converge to the best solution with a high probability.

For the band selection problem we concerned, the number of selected bands in a hyperspectral image must firstly be determined. The following step is to seek the effective band combinations [24]. However, it is not applicable to enumerate all possible band combinations and to test their classification performance since there are hundreds or even thousands of bands in the hyperspectral image. The computational workloads will grow exponentially as bands increase. Therefore, we use ICS method to solve the band selection problem by converting it into an optimization issue. The ICS-based algorithm is expected to significantly reduce computational complexity and to be highly accurate for hyperspectral image classification.

In order to select effective bands by using ICS, the initial step is to establish the affinity function (the objective function to be optimized). Considering some criteria for classification, we search for a method by which to build the affinity function, for instance, the spectral separability (including Euclidean distance, spectral angle mapper, and spectral correlation mapper) and the band information redundancy (including band correlation). By building the affinity function, in this paper, we propose a new algorithm, ICS-EBS (ICS-based effective band selection), which can be used in the classification of a hyperspectral image. We used hyperspectral data obtained from the Washington D.C. Mall and Northwest Tippecanoe County to evaluate the proposed algorithm. The experimental results indicate that our proposed algorithm obtained good performance and a robust classification.

This paper is organized as follows. In Section II, we briefly introduce the ICS. Some band selection criteria for hyperspectral image classification are discussed in Section III. In Section IV, our proposed algorithm based on ICS is described in details. The experiments, results, and analysis are presented in Section V. Finally, Section VI gives a concise summary and discussion of our work.

### II. ICS FOR EFFECTIVE BAND SELECTION

Immune clonal strategy is based on the theory of clonal selection, which describes the mechanisms of the natural immune response to antigenic invasions [22]. When antigens invade an organism for the first time, they can stimulate immunocytes to perform clonal multiplications mainly involving clone, mutation, selection, etc. Clonal selection corresponds to a process of affinity maturation and the mature antibodies can be preserved as memory cells. When the same type of antigen invades again, immunocytes can produce high affinity antibody cells to eliminate them and the immune response is stronger, faster, and more effective [25], [26].

Immune clonal strategy imitates the dynamic learning mechanisms of the immune system and can be applied to real problems. Generally, the antigen cells are regarded as problems, while the antibody cells are treated as solutions to the target problems. The combining power between the antibody and the antigen, which illustrates the effectiveness of the solution, can be measured by using an affinity function. For the problem of concern in this paper, the antigen cells can be treated as the problem of hyperspectral image classification and the antibody cells can be regarded as the effective band combinations. The process of immune clonal strategy is to seek continuously the antibody with the best affinity for the antigen.

Given a set of antibody population, i.e., possible band combinations pool $Ab$ and continuous bands $B$, which are denoted as $Ab = \{ab_1, ab_2, \cdots, ab_N\}$ and $B = \{b_1, b_2, \cdots, b_N\}$, respectively, where $N$ is the size of the antibody population and $N_a$ is the total number of bands in hyperspectral image. We want to select the effective band combinations, and the state transfer of the antibody population based on ICS is given as follows, where $ab_i \subset B$ ($i = 1, 2, \cdots, N$):

$$Ab(k) \xrightarrow{C} Ab'(k) \xrightarrow{M} Ab''(k) \xrightarrow{Sel} Ab'''(k) \xrightarrow{Sup} Ab(k+1).$$

C: Clone, M: Mutation, Sel: Selection, and Sup: Supplement

It should be noted that we also use supplement operator in ICS, which will be explained in more details in Section IV-B4.

### III. BAND SELECTION CRITERIA FOR CLASSIFICATION

The initial step of using ISC is to establish the affinity function. Therefore, some band selection criteria for hyperspectral image classification have to be defined. These criteria could further be used to establish the affinity function, which will be described in more details in Section IV-A.

In general, band selection needs to consider the following characteristics: target reflectance properties, solar spectrum curve, atmosphere, sensors, and final data application [27]. Usually, we will preserve the representative bands that are acquired under similar solar and atmospheric conditions, and initially remove some useless bands according to the former four data attributes (i.e., target reflectance properties, solar spectrum curve, atmosphere, and sensors). With respect to the data application, we consider several classification criteria, such as spectral separability, including Euclidean Distance, Spectral Angle Mapper, and Spectral Correlation Mapper, and the band information redundancy, including Band Correlation.
A. Euclidean Distance (ED)

ED [28] is a widely used geometric-based vector-distance measurement. The ED between two vectors is the Euclidean magnitude of the squared subtractive difference vector. The ED is defined as:

$$ED(X, Y) = \sqrt{\sum_{k=1}^{N_b} (X_k - Y_k)^2},$$  \hspace{1cm} (1)

where $X$ and $Y$ are spectral vectors with $N_b$ (i.e., number of bands) dimensions. This metric responds independently of a general linear transformation of the two vectors (i.e., gain or offset). The ED is insensitive to gain factors, which can be viewed as one of its advantages. However, it is obvious that a simple measure of the ED is incapable of distinguishing between magnitude and direction.

B. Spectral Angle Mapper (SAM)

SAM [29] is a geometric-based vector-angle measurement that mainly responds to the similarity in shape between the two vectors. The SAM is defined as:

$$SAM(X, Y) = \arccos \left( \frac{X^T \cdot Y}{||X|| \cdot ||Y||} \right),$$ \hspace{1cm} (2)

where $X$ and $Y$ are two $N_b$-dimensional spectral vectors, $X^T$ indicates the transposition of $X$, $||X||$ represents the magnitude of $X$, and $||Y||$ represents the magnitude of $Y$. The SAM is insensitive to gain factors, which can be viewed as one of its advantages. However, the SAM technique will fail in many cases if the vector magnitude is important.

C. Spectral Correlation Mapper (SCM)

SCM [30] is a statistically based vector-correlation measurement that measures the strength of the linear relationship between two vectors, and responds independently of a general linear transformation of the two vectors (i.e., gain or offset). The SCM is defined as:

$$SCM(X, Y) = \frac{\sum_{k=1}^{N_b} (X_k - \mu_X) \cdot (Y_k - \mu_Y)}{(N_b - 1) \cdot \sigma_X \cdot \sigma_Y},$$ \hspace{1cm} (3)

where $X$ and $Y$ are $N_b$-dimensional spectral vectors, $\mu_X$ and $\sigma_X$ represent the mean and standard deviation of vector $X$, respectively, and $\mu_Y$ and $\sigma_Y$ represent the mean and standard deviation of vector $Y$, respectively. Unlike the SAM method, the SCM technique can be applied to images with a negative correlation. However, the correlation coefficient is incapable of explicitly defining vector difference.

D. Band Correlation (BC)

BC [31] is also a statistically based vector-correlation measurement that indicates the information redundancy of each spectral band. The BC is defined as:

$$BC(i, j) = \frac{\sum_{p=1}^{N_b} (x_{ip} - \mu_i) \cdot (x_{jp} - \mu_j)}{\sqrt{\sum_{p=1}^{N_b} (x_{ip} - \mu_i)^2} \cdot \sqrt{\sum_{p=1}^{N_b} (x_{jp} - \mu_j)^2}},$$ \hspace{1cm} (4)

where $BC(i, j)$ is the correlation coefficient of bands $i$ and $j$, $x_{ip}$ and $x_{jp}$ are the $p^{th}$ pixel value of bands $i$ and $j$, respectively, and $\mu_i$ and $\mu_j$ represent the mean of bands $i$ and $j$, respectively.

IV. PROPOSED METHODOLOGY

In this section, we propose a new separability criterion for effective bands selection. This criterion is needed for further establishing the affinity function. Then, some of the main immune operators used in this paper are described in details. Finally, a new algorithm for band selection by using ICS will be proposed. The selected bands can be used in hyperspectral image classification.

A. Affinity Function Based on A New Separability Criterion

Driven by classification accuracy, all four criteria given in Section III-A to Section III-D have been considered in this paper. Specifically, the spectral separability of different objects has been considered in the first three criteria, and the spectral information of different bands has been concerned in the fourth criterion. Therefore, we propose a new measurement of separability for band selection involving all four criteria, and is given by:

$$sepIndex = \frac{SCM \cdot BC}{ED \cdot SAM},$$ \hspace{1cm} (5)

where $sepIndex$ is the measurement of separability, and $SCM$, $BC$, $ED$, and $SAM$ are given by the Eq.(1) to Eq.(4), which are all normalized to the interval (0, 1). Generally, larger values of ED and SAM and smaller values of SCM indicate better separability, while smaller BC values mean less information redundancy. From Eq.(5), we know that the smaller $sepIndex$ presents a better classification of the different objects. It should be noted that the issue of spectral separability for hyperspectral image classification is a multi-objective optimization problem as there are four individual components need to be optimized, but we don’t intend to develop the proposed ICS for the multi-objective optimization. Instead, we just reasonably combine the four components into one equation in Eq.(5). The reason is that as the authors have addressed in [32], [33], the extension of evolutionary algorithms to the multiple objective case has mainly been concerned with multi-objective fitness assignment. In this paper, we just focus on establishing an affinity function in order to use ICS to select effective bands. To investigate how the each individual component contributes to the fitness assignment is beyond the scope of this paper.

Considering the goal of the proposed algorithm based on ICS, which is to maximize the objective function, the affinity function can be established based on the proposed separability criterion. The affinity function is limited to the interval (0, 1), and is defined as follows:

$$Aff = \frac{1}{1 + sepIndex},$$ \hspace{1cm} (6)

where $Aff$ can be regarded as the measurement of combination power between the antigen and antibody. It is obvious that a larger $Aff$ indicates a better combination (which means a better classification result).

B. Immune Operators

In this section, we employed the immune clonal strategy and redefined/modified some immune operators under the
framework of artificial immune systems to solve the specific problem—effective band selection. To be specific, we redefined the clone operator, selection operator, and supplement operator in our paper in order to accomplish easy implementation, but we followed the general description and mathematical definition in [22] and [23], respectively. Inspired from [25], we modified the mutation operator for the selection of effective bands we have concerned in this paper.

1) Clone Operator: The clone operator aims at the self-copy of the antibody population, and the clone number of each antibody is calculated according to its affinity. Let $Ab$ present the antibody population, which is denoted as $Ab(k) = \{ab_1, ab_2, \ldots, ab_N\}$, where $N$ is the size of antibody population. In this paper, the used clone operator $T^c_c$ is defined as follows:

$$T^c_c(ab) = [T^c_c(ab_1), T^c_c(ab_2), \ldots, T^c_c(ab_N)] = Ab'(k),$$

where $T^c_c(ab)(i = 1, 2, \ldots, N)$ is the clone of the antibody $ab_i(ab_i \in Ab(k))$. The clone number of each $ab_i$ is given by:

$$N_{CI} = 1 + \lfloor \text{norAff}_f \cdot N \rfloor, \quad (7)$$

where $N_{CI}(i = 1, 2, \ldots, N)$ represents a clone number of $ab_i$. $\lfloor \cdot \rfloor$ is floor function, and $\text{norAff}_f(i = 1, 2, \ldots, N)$ is the normalized affinity of $ab_i$.

2) Mutation Operator: The mutation operator aims at determining the optimal solution in space $B$, and the strategy of mutation is also related to the affinity of $ab_i$. In this paper, the used mutation operator $T^c_M$ is defined as follows:

$$T^c_M(ab) = [T^c_M(ab_1), T^c_M(ab_2), \ldots, T^c_M(ab_N)] = Ab''(k),$$

where $T^c_M(ab)(i = 1, 2, \ldots, N)$ is a mutation of antibody $ab_i(ab_i' \in Ab'(k))$.

In order to improve the effect of mutation, we adopt a hybrid mutation strategy. Specifically, the antibody takes different mutation strategies in response to different affinities for $ab_i$. For those $ab_i(i = 1, 2, \ldots, p)$ that have a high affinity, we adopt a low-frequency mutation strategy to their clone population, since it might be close to the best solution. However, for the remaining $ab_i(i = 1, 2, \ldots, q, s.t. : p + q = N_{CI})$, which have a low affinity, we take a high-frequency mutation strategy, since it might be far beyond the best solution.

In this paper, the mutation strategies for antibodies with both high and low affinity are based on real-value encoding. Specifically, suppose that the antibody encoded with a real value, and is denoted as $ab_i = \{b_1, b_2, \ldots, b_{N_S}\}$, where $b_i \in B$ and $N_S$ is the number of selected bands. The low-frequency mutation, namely a single-point mutation, can be realized as the following operations: randomly choosing one element in $ab_i$, such as $b_k(k = 1, 2, \ldots, N_S)$, and then replacing it with a random $b_l(b_l \in [b_k - \delta, b_k + \delta])$, where $\delta$ is an integer and represents the mutation step. The high-frequency mutation, namely a multi-point mutation, can be realized similarly to the single-point mutation: choosing all elements instead of one in $ab_i(ab_i = \{b_1, b_2, \ldots, b_{N_S}\})$, and for each $b_k(b_k \in ab_i, k = 1, 2, \ldots, N_S)$ repeating the same process of single-point mutation.

3) Selection Operator: The selection operator aims at preserving optimal antibodies as memory cells, and the strategy of section is related to the affinity of $ab_i(ab_i \in Ab(k))$. In this paper, the used selection operator $T^c_s$ is defined as follows:

$$T^c_s(ab') = \{T^c_s(ab'_1), T^c_s(ab'_2), \ldots, T^c_s(ab'_{N_S})\} = Ab''(k),$$

where $T^c_s(ab'_i) = \{ab'_j\}(i = 1, 2, \ldots, N_S, j = 1, 2, \ldots, N_{MI})$ is the selection of antibody $ab'_j(ab'_j \in Ab''(k)), and \quad N_{MI}(i = 1, 2, \ldots, N)$ is the selected number of each $ab_j$, in which $N_{MI}$ is given by:

$$N_{MI} = \lfloor \text{mean}(\text{norAff}_M(i)) \cdot N_{CI} \rfloor, \quad (8)$$

where, $\lfloor \cdot \rfloor$ is the ceil function, $\text{mean}(\cdot)$ is the mean of $\text{norAff}_M, \text{norAff}_M(i = 1, 2, \ldots, N)$ is a normalized vector with an affinity of $ab_i$, and $N_{CI}$ is the clone number of $ab_i$.

4) Supplement Operator: Other operators besides those listed above are defined in ICS, such as supplement and vaccination operator [20], [22]. In order to increase the diversity of the antibody population and to avoid local convergence, in this paper, the used supplemental operator $A^c_S$ is taken into account, which is defined as follows:

$$A^c_S(ab) = \{ab_1, ab_2, \ldots, ab_{N_S}\} = Ab_{add}(k),$$

where $A^c_S(ab)$ is the supplement of the antibody population $Ab$, and $N_k$ is the total supplement number of the $k^{th}$ iteration, and is given by:

$$N_k = \lfloor ab_{N_k} \cdot \exp\left(-\sqrt{k/gemMax}\right) \rfloor, \quad (9)$$

where $N_k(k = 1, 2, \ldots, genMax)$ is the supplement number of the generation, $\lfloor \cdot \rfloor$ is defined in Eq.(7), $ab_{N_k}$ is the number of antibodies in the $k^{th}$ generation, and $genMax$ is the maximum iteration time.

C. ICS-Based Effective Band Selection Algorithm

We propose a new algorithm, ICS-EBS (ICS-based effective band selection), which is used in further classification of a hyperspectral image. A flow chart of the proposed algorithm is shown in Fig. 1, and the details of the algorithm process are described below.

**Step 1**: Initialization: Create an initial antibody population randomly and obtain $N_{init}$ antibodies denoted as $Ab_{init}(k) = \{ab_1, ab_2, \ldots, ab_{N_{init}}\}|(ab_i \subset B)$, where $ab_i(i = 1, 2, \ldots, N_{init})$ contains a random combination of spectral band numbers in space $B (B = \{b_1, b_2, \ldots, b_{N_B}\})$, and the number of selected bands $N_k$ can be determined upon experience, considering different scenes in hyperspectral image classification.

**Step 2**: Initial Selection: Calculate the affinity of each antibody $ab_i(ab_i \in Ab_{init}(k))$ by using Eq.(6). Then, select the first $N$ antibodies from $Ab_{init}(k)$, where each antibody $ab_i$ in $Ab_{init}(k)$ is descended by its affinity. In this way the initial select antibody population $Ab(k)$ has been formed.

**Step 3**: Clonal Proliferation: Perform reproduction of each antibody $ab_i(ab_i \in Ab(k))$. Its clone number is $N_{CI}$, which can be calculated by using Eq.(7). In this way the clonal antibody population $Ab(k)$ has been formed with the size of the antibody population being $N_C(N_C = \sum_{i=1}^{N} N_{CI})$. 

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Step 4: Hybrid Mutation: To some antibodies \( \{ab'_i\} (ab'_i \in Ab' (k), i = 1, 2, \ldots, p) \) with high affinity, we adopt a single-point mutation, while to others \( \{ab''_i\} (i = 1, 2, \ldots, q, s.t.: p + q = N_C) \) with low affinity we adopt the multi-point mutation. In this way the mutational antibody population \( Ab'' (k) \) has been formed. The strategy for using both the single-point and the multi-point mutations has been discussed in Section IV-B2.

Step 5: Memory Selection: Calculate the affinity of each antibody \( ab''_i \) \( (ab''_i \in Ab'' (k)) \) by using Eq.(6). Then, select the first \( N_{Mi} \) of each \( \{ab''_i\} \) in order of descending affinity. The selected number is \( N_{Mi} \), which can be calculated by using Eq.(8). In this way the memorial antibody population \( Ab'' (k) \) has been formed with the size of the antibody population being \( N_M (N_M = \sum_{i=1}^{N} N_{Mi}). \)

Step 6: Antibody Supplement: Create a new antibody population randomly and get \( N_k \) antibodies denoted as \( Ab_{add}(k) = \{ab_1, ab_2, \ldots, ab_{N_k}\} (ab_i \in B, i = 1, 2, \ldots, N_k) \). The supplement number is \( N_k \), which can be calculated by using Eq.(9). In this way, the new antibody population \( Ab(k+1) \) has been formed for the next iteration (i.e., \( Ab(k+1) = Ab_{add}(k) \cup Ab'' (k) \)).

Fig. 2: False-color image of Washington D.C. Mall

Step 7: Iteration: Repeat Steps 2 to 6 until \( k \) has reached the maximum number of iterations. In this way the antibody with the highest affinity, namely the effective bands combination, has been calculated and is denoted as \( ab_{Best} = \{b_1, b_2, \ldots, b_{N_k}\} (b_i \in B, i = 1, 2, \ldots, N_k). \)

Step 8: Classification: Use the effective band combination \( ab_{Best} \) to perform classification of the given hyperspectral image.

V. Experiments & Results

In this section, the proposed algorithm is used to obtain the effective band combinations in hyperspectral image, and then the results are applied to classification. The experimental results, their interpretation, and their analysis are also given in this section.

A. Data Preparation

1) Washington D.C. Mall Data Sets: The image was collected by using the hyperspectral digital imagery collection experiment (HYDICE) sensor on August 23, 1995. Each channel had 1,280 lines with 307 pixels each. The original data include 210 bands in the 0.4 to 2.4 \( \mu m \) region. Because the bands from the near-infrared and infrared wavelengths have more noise than bands from the visible wavelengths, 19 noisy bands have been removed. A thematic map with ground truth labels for 8,079 pixels is supplied with the original data, and seven information classes have been defined, namely: roof, street, path, grass, tree, water and shadow. The image was sectioned into 562 rows by 307 columns by 191 bands from the original image. The false-color image with bands 63 (R), 52 (G) and 36 (B) is presented in Fig. 2.

2) Northwest Tippecanoe County Data Sets: The image was collected by using the airborne visible/infrared imaging spectrometer (AVIRIS) sensor on June 12, 1992. Each channel
had 2,678 lines with 614 pixels each. The original data include 224 bands in the 0.4 to 2.4 \( \mu m \) region, but 4 noisy bands have been removed. A thematic map with ground truth labels for 334,245 pixels is supplied with the original data. Because most of the ground area is covered by vegetation, without loss of generality, four different classes, namely: orchard, river, woods and pond are selected as target objects for classification. The image was sectioned into 200 rows by 200 columns by 220 bands from the original image. The false-color image with bands 50 (R), 27 (G) and 17 (B) is presented in Fig. 3.

### B. Description of Comparison Methods

The proposed algorithm, ICS-EBS, was evaluated by using the Washington D.C. Mall data sets and Northwest Tippecanoe County data sets. In this paper, the proposed algorithm was compared against one latest proposed band selection algorithm, Inter-Class Separability Index Algorithm (ICSIA) in the literature [34]. Considering that ICS is the stochastic algorithm, we also compared the results with those obtained by other stochastic algorithms, including Genetic Algorithm (GA) and Ant Colony Optimization (ACO).

The ICSIA uses subspaces-based partition theory to narrow down the possible band combination set [35]. Then, the ICSIA evaluates the performance of all possible band combinations via employing three spectral separability criteria — Euclidean Distance, Spectral Angle Mapper, and Spectral Correlation Mapper. Finally, the ICSIA uses the best combination bands as the selected band set which is used for classification in the further step.

There are several popular evolutionary algorithms that have been proposed in the last decades, such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Artificial Bee Colony (ABC). Different from GA and ACO, PSO, DE, and ABC are born to deal with the continuous problems. In this paper, therefore, we employed GA and ACO as the comparison algorithms against with ICS to select effective bands.

For fair comparison, we set the all the parameters in the proposed algorithm as well as GA and ACO to be fixed for the two investigated hyperspectral data sets. The values of common parameters were set as follows: the population size \( N_{\text{pop}} = 80 \) and the maximum iteration times \( \text{genMax} = 35 \). For ICS-EBS, the initial antibody population \( N_{\text{Init}} = 80 \), the initial selected antibody population \( N = 50 \), and the mutation step \( \delta = 5 \). For GA-based effective band selection (GA-EBS), the crossover probability \( P_C = 0.7 \), and the mutation probability \( P_M = 0.05 \). For ACO-based effective band selection (ACO-EBS), the evaporation rate \( \rho = 0.8 \), constant \( Q = 100 \), and the control parameters \( \alpha = 1 \) and \( \beta = 5 \).

### C. Experimental Results and Analysis for Washington D.C. Mall Data Sets

In the conducted experiments, we choose seven and eight respectively as selected bands number for ICSIA. The reason that we choose band combinations starting from seven is that the selected bands should be sufficient to accommodate the specific problem. In addition, because of the limitation of using subspaces-based partition theory, in this case, ICSIA can only select eight bands at most. For fair comparison, we also choose \( N_b = 7 \) and \( 8 \) for GA-EBS, ACO-EBS, and ICS-EBS, respectively, and then we use the same classification method in [34] to achieve comparison on classification results. Unlike ICSIA, GA-EBS, ACO-EBS, and ICS-EBS has no restriction of selected bands number, but the classification accuracy is not simply enhanced as the selected bands number increased. Therefore, we choose \( N_b = 11 \) for GA-EBS, ACO-EBS, and ICS-EBS in order to give an easy and convenient comparison with ICSIA.

The effective band combinations calculated by ICSIA with \( N_b = 8 \) are: 33, 43, 55, 61, 62, 101, 112, and 171. The effective band combinations selected by the proposed algorithm with \( N_b = 11 \) are: 2, 39, 48, 68, 69, 70, 79, 80, 137, 138, and 191. The classification results of ICS-EBS with \( N_b = 11 \) are shown in Fig. 4. The comparison results of producer’s, user’s, and overall accuracy rates of the classification for each class
TABLE I
ACCURACY RATE AND KAPPA COEFFICIENT OF CLASSIFICATION FOR WASHINGTON D.C. MALL DATA SETS

<table>
<thead>
<tr>
<th>(N_b)</th>
<th>Producer’s Accuracy Rate for Each Class (%)</th>
<th>User’s Accuracy Rate for Each Class (%)</th>
<th>Overall</th>
<th>Kappa</th>
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<td>79.40</td>
<td>99.52</td>
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<tr>
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<td>8</td>
<td>71.43</td>
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<tr>
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<td>11</td>
<td>94.04</td>
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</tbody>
</table>

R: Roof, St: Street, P: Path, G: Grass, T: Tree, W: Water, S: Shadow

Fig. 5. ICS-EBS classification results for Northwest Tippecanoe County data sets with \(N_b = 5\)

as well as the Kappa coefficients are given in Table I. Note: Kappa coefficient is a measure of agreement or association for the conducted experiments.

A total of 4,493 pixels with seven different class labels were used to evaluate the performance of ICS-EBS and other three comparison algorithms. From Table I, we can see the producer’s and user’s classification accuracy of ICS-EBS are higher than ICSIA, GA-EBS, ACO-EBS with \(N_b = 7\) and \(8\) on most classes. Moreover, with no restriction of selected bands number and compared with GA-EBS and ACO-EBS, ICS-EBS can obtain a better classification results with \(N_b = 11\). The overall accuracy rates of the classification from Table I show that ICS-EBS outperforms ICSIA, GA-EBS, and ACO-EBS with overall performance. The Kappa coefficients from Table I also indicate that the classification results of ICS-EBS has a better consistency compared with that of the other three comparison algorithms.

D. Experimental Results and Analysis for Northwest Tippecanoe County Data Sets

In the conducted experiments, we choose four and five respectively as selected bands number for ICSIA. Likewise, the classification results of ICS-EBS are compared with ICSIA, GA-EBS, and ACO-EBS.

The effective band combinations calculated by ICSIA with \(N_b = 5\) are: 2, 4, 98, 106, and 163. The effective band combinations selected by the proposed algorithm with \(N_b = 5\) are: 27, 28, 29, 31, and 54. The classification results of ICS-EBS with \(N_b = 5\) are shown in Fig. 5. It should be noted that the Fig. 5 just shows the classification results for the area of selected classes. The comparison results of producer’s, user’s, and overall accuracy rates of the classification for each class as well as the Kappa coefficients are given in Table II.

A total of 5,738 pixels with four different class labels were used to evaluate the performance of ICS-EBS and other three comparison algorithms. From Table II, we can see the producer’s and user’s classification accuracy of ICS-EBS are better than ICSIA, GA-EBS, ACO-EBS on most classes. The overall accuracy rates as well as Kappa coefficients from Table II also illustrates that ICS-EBS outperforms ICSIA, GA-EBS, and ACO-EBS.

VI. SUMMARY & DISCUSSION

Reducing the redundancy of spectral information is a significant task in the classification of hyperspectral image. For example, in the experiment conducted in Section V-C, if we want to select effective 11 bands from total 191 bands, we have to compute about \(10^{11}\) possible combinations. There is some early work by CD Bocaniala in [36] which developed a fuzzy classifier to be used for fault diagnosis task in industrial devices. Different from the reference paper, we proposed an evolutionary-based classifier for objects classification in the hyperspectral image. To be specific, in this paper, we therefore successfully introduce the intelligence-based computation,
ICS, into the field of effective band selection for hyperspectral image classification to improve the search ability. Compared with the traditional methods, ICS has the ability to self-learn, identify, and memorize. In order to use the ICS, an affinity function must firstly be established, and this has a great influence on the performance of the proposed algorithm. Two aspects of the method, spectral separability and band information redundancy, are mainly taken into account in this paper. Then we used Washington D.C. Mall data sets and Northwest Tippecanoe County data sets to evaluate the proposed algorithm. In the conducted experiments, the proposed new algorithm, ICS-EBS, improves the accuracy rate for hyperspectral image classification in terms of overall performance, and has no restriction of selected bands number. From Table I and Table II, we can see that the proposed algorithm has higher accuracy rates especially for classification with more classes. Thus, compared with using GA and ACO for solving EBS, the proposed algorithm can select the effective band combination. The relative inferior results of using GA and ACO on the conducted experiments may due to their poor searching performances within the given iterations and population size, but it should be noted that more function evaluations and large population size lead to a heavy computation burden.

However, the accuracy of the classification is not as high as we expected as the affinity function might not precisely reflect the separability of different objects in the various situations especially when the reference spectra are very similar among different objects. Therefore, a future study will focus on establishing better affinity functions so as to be more suitable to hyperspectral image classification in which different scenes are present. In addition, ICS-EBS can be used in the real time, and it is expected to be tested on the performance of hardware implementation in our future work.

REFERENCES
