DIMENSIONAL REDUCTION IN HYPERSPECTRAL IMAGES BY DANGER THEORY BASED ARTIFICIAL IMMUNE SYSTEM

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KEY WORDS: Agriculture, Hyper spectral, Extraction, Classification, Artificial_Intelligence, Algorithms

ABSTRACT:

A new dynamical dimensional reduction model (HDRM) for hyperspectral images is proposed based on clone selection algorithm which is inspired from nature immune system in this paper. In existing dimensional reduction method, feature selection is most inefficient. To improve the efficiency, the feature selection problem in hyperspectral images is taken as a multi-objective optimization problem. The feasible band sets are regarded as antibodies and the evaluation criteria in feature selection are regarded as the antigens in HDRM. Go through generation after generation, the sets keep on evolution under the guidance and constrain of evaluation criteria, ultimately, the optimization sets can be found. The model is trained with a hyperion image data, and the result of feature selection is used in classification to test its effect. It is proved that the time cost in feature selection is 100s in the experiment data, and the iterate time is just 10 when β is 0.631, ω is 0.873.

1. INTRODUCTION

Resent Years, as the sensor technology's advance, hyperspectral image has got unprecedented development. The applications of hyperspectral image data have extended to agriculture, environment, mine, and so on. Because hyperspectral image data could provide much higher resolution than normal remote data. And their resolution can reach nanometer. The ground objects and their characteristics can be discriminated more accurately by hyperspectral image data.

The quantity of the bands of the hyperspectral image data is very large, and the correlation of the bands is quite strong, too. On one hand, the hugeness of the data brings difficulties to not only data storage, but also data processing. It holds back the applying of the hyperspectral image data in some degrees. On the other hands, traditional methods which have been designed for multi-spectral image data can not be easily applied to hyperspectral image data. So, dimensional reduction in hyperspectral image data without losing important information about objects of interest has become a topic of a substantial amount of research in recent years.

In many objects, their reflectance or absorption characteristics only appear at a very narrow spectral range. The correlation between the bands is quite strong, too. So, dimensional reduction in hyperspectral image data is theoretically feasible. This bas been investigated by Jimenez (Zhao, 2004) in detail. Roughly speaking, the common ways for dimensional reduction fall into two categories: One is feature extraction; and the other is feature selection (Zhao, 2004). The process of feature extraction is usually fast, but the original spectral properties of the image are lost after the extraction. Feature selection always costs longer time, but the spectral properties of the image are remained. When the evaluation criteria for the optimized band set are determined, feature selection could be regarded as a combinational optimization problem. The immune system contains the abilities of self-tissue, self-cognition, self-memory, clone mutation, and so on. These abilities provide combinational optimization new ideas. Castro and Timmis (De Castro, 2002) have built an Artificial Immune Network for multimodal function optimization. Li investigates AIS in global optimization, too (Li, 2005). Based on these researches, the concept of AIS is introduced to hyperspectral image data. To improve the efficiency of feature selection, this paper derives some important algorithms from AIS for dimensional reduction, and proposes a hyperspectral dimensional reduction model (HDRM).

In the process of hyperspectral data dimensional reduction, some prior information could be excavated. When prior information is useful, we get some structural characters of the hyperspectral data, with which as the guiding, the dimension can be reduced effectively and gradually in hyperspectral data. And the threshold value could be set to and the process. All of this can be looked as a process of recognition. We can take the prior information as the primary immune response, and the process of the hyperspectral data reduction can be took as the secondary immune response, during which the self- tissue, self-cognition, self-memory and other abilities can be inspired.

This paper is organized as follows. Section 2 is a brief introduction to clonal selection theory which is derived from AIS, and it gives a short description of multi-objective optimization, too. Section 3 presents a model (HDRM) to reduce the dimension of hyperspectral data. In Section 4, an experiment based on HDRM is carried out in a hyperion image. Then the results are provided and discussed. Section 5 concludes the entire work and presents prospects of AIS in hyperspectral image data process and the future works needed to do.

2. THE CLONAL SELECTION IN MULTI-OBJECTIVE OPTIMIZATION PROBLEM

AIS is a calculation model AIS inspired from theoretical biology, it makes use of some functions, principles and models

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from nature immune system to solve complex problems (Timmis, 2001).

The natural immune system consists of immune organs, immune cells and immune molecules. Immune organs are composed of central immune organs and peripheral immune organs. Central immune organs are composed of bone marrow and thymus, where lymphocytes and other immune cells generate, differentiate and mutate. Peripheral immune organs include lymphocytes, spleen, and catarrh tissues, where T-cell and B-cell settle and proliferate, and where immune system responds to antigen's stimulation.

AIS provides new ideas for multi-objective optimization. Chung et al (J.S.Chung, 1998) confirmed that immune algorithm were superior to other algorithms in solving multi-objective optimization problems. Then the research on immune algorithm has absorbed significant attention in recent years (Zhang, 2006). Clonal selection algorithm is an excellent immune algorithm in AIS, and has been tested useful in multi-objective optimization.

2.1 The clonal selection algorithm

In 1950s, the clonal selection theory was developed by Burnet for the first time (Burnet, 1959). De Castro then proposed a clonal selection algorithm (De Castro, 2002) which was based on the clonal selection theory. The algorithm is mentioned briefly as Figure 1.

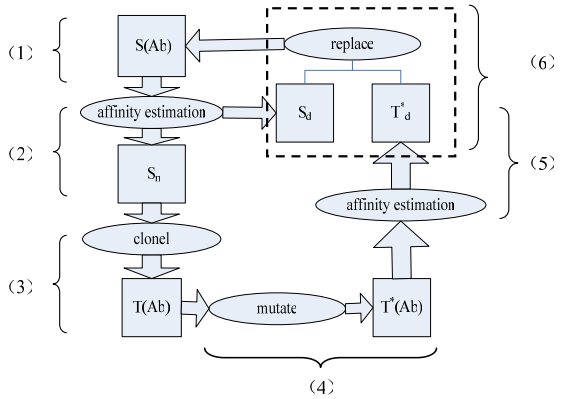

Figure 2. Diagram of the clonal selection algorithm

Step1: Produce original population S(Ab), which is a set of antibodies.

Step2: Select n best individuals S_n from original population through affinity estimation.

Step3: Clone these n best individuals, and generate temporary population T(Ab). The clone size increases as the increasing of the affinity.

Step4: A mutation operation is used to temporary population T(Ab), and a mature mature population T^*(Ab) is generated.

Step5: Select d best individuals from T^*(Ab), and a set T^*_d is composed.

Step6: Replace d worst individuals from original population S(Ab) by T^*_d, and a clonal selection of S(Ab) is completed.

2.2 Immune algorithm in multi-objective optimization

2.2.1 The definition of multi-objective optimization problem: Multi-objective optimization problem is that find the decision variable which satisfies constrains and optimizes the objective functions. A typical multi-objective optimization problem with n decision variables, m constrains and p objectives are described as formula (1).

$$\min F(x) = \left[f_1(x), f_2(x), \ldots, f_p(x)\right]^T$$
$$\text{s.t. } g_i(x) \le 0, i = 1,2,\ldots,m \quad (1)$$

$X = \{x \mid g_i(x) \le 0, i = 1,2,\ldots,m\}$ which is constrained domain is said to the feasible domain of decision variables.

Pareto optimal solution: the optimal solution is always a set in multi-objective optimization problems, so pareto optimal solution is an important concept which is described as formula (2).

X^* is a Pareto optimal solution if and only if there exist no other variable X, which satisfies the expression as below when it does not contravene the constrains:

$$\forall i \in \{1,2,\ldots n\}: f_i(X) \le f_i(X^*) \wedge \exists$$
$$j \in \{1,2,\ldots n\}: f_j(X) \prec f_i(X^*) \quad (2)$$

2.2.2 Immune algorithm in multi-objective optimization: In multi-objective optimization problems, a feasible solution could be treated as an antibody, and an object function could be treated as an antigen. The affinity between antibody and antigen could be described as the value of the object functions for feasible solutions (Figure 2).

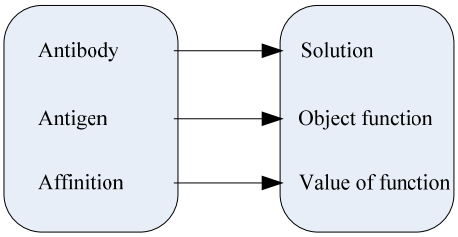

Figure 2. The reference from immune system to multi-objective optimization problem

Immune memory is contained in clonal selection algorithm. It makes sure the fast convergence of global optimal solution. The clonal proportion conforms to direct ratio with affinity. Then through the mutation, it promotes or inhibits the antibodies. It shows the self-adjustment ability of immune system. There are two forms to calculate the affinity: one reflects the correlation between antibodies and antigens (the matching degree between solution and objects), and the other one reflects the correlation between antibodies and antibodies, which ensures the diversity of antibody in immune system (Zhai, 2006).

In addition, the clonal select algorithm can control the quantity of the same antibodies by calculating the expected survival value. It contains a memory cell set which saves the better antibodies, so the immune algorithm can converge very fast.

3. THE DIMENSIONAL REDUCTION MODEL IN HYPERSPECTRAL IMAGE

3.1 Evaluation criteria during the process of feature selection

In feature selection, many indexes are designed to evaluate the selected bands. There are Joint entropy, determinant of covariance matrix, Bhattacharyya distance, OIF (Optional Index Factor), and so on (Swain P H, 1987; Sheffield C, 1985; Chavez P S, 1982). In this paper, OIF is used as the evaluation criterion.

$$OIF = \frac{\sum_{i=1}^{n} S_i}{\sum_{i=1}^{n}\sum_{j=i}^{n}\left|R_{ij}\right|} \tag{3}$$

In the above formula, S_i is the standard deviation of the ith band, and R_{ij} is the correlation coefficient between the ith band and the jth band.

The amount of information of the selected bands conforms to direct ratio with OIF value of bands set.

3.2 The mathematical expression of feature selection problem

Suppose that P is the number of bands in the image, and λ is the wavelength. All the wavelengths construct the Set $S_\lambda = \{\lambda_1, \lambda_{2,} \ldots \lambda_p\}$. The progress of feature select will select N bands from S_λ, and the result can be expressed as $\vec{\lambda} = \{\lambda_1, \lambda_{2,} \ldots \lambda_N\}$. The entire probable $\vec{\lambda}$s constitute a set $S(m)$. Then the object function $F(\vec{\lambda})$ could describe the progress of calculating OIF value of the selected bands i.e. $\{\lambda_1, \lambda_{2,} \ldots \lambda_N\}$. Feature selection problem can be described in math as formula (4).

$$\begin{aligned} &\min F(\vec{\lambda}) = OIF \\ &\text{s.t.}\ \vec{\lambda} \in S(m) \end{aligned} \tag{4}$$

Select $\vec{\lambda}$ from $S(m)$, and the $\vec{\lambda}$ should minimize $F(\vec{\lambda})$. $\vec{\lambda}$ is the decision variables($\vec{\lambda} = \{\lambda_1, \lambda_{2,} \ldots \lambda_N\}$), constrain domain $\lambda = \{\lambda \mid \lambda_i \in S(m), i = 1,2,\ldots,m\}$ is said to the feasible domain of decision variables. The formula of calculating OIF has been shown on formula (3).

Feature selection problem has been transformed to an optimization problem under the constrain domain of S(m). Thus, it can be proved that dimensional reduction problems are multi-objective optimization problems.

3.3 Hyperspectral dimensional reduction model

Inspired of immune system, this paper has built a Hyperspectral dimensional reduction model on the base of clonal selection algorithm. HDRM is displayed as below:

1) All the wavelengths construct the set S_λ, and N bands constitute individual (feasible solution) $\vec{\lambda}$. In the space $S(m)$ which is constituted of all the probable $\vec{\lambda}$, Select M $\vec{\lambda}$ from $S(m)$ to constitute original population $S(\vec{\lambda})$, which is a set of antibodies. With no influence on the result, λ_i (i.e. the elements of $\vec{\lambda}$) are arranged from large to small.

2) Select n best individuals to constitute a set S_n from $S(\vec{\lambda})$ through calculating the value of $F(\vec{\lambda})$. On the progress of calculating $F(\vec{\lambda})$, the $\vec{\lambda}$ is referenced to the wavelengths λ_i, and then to the corresponding images. So the OIF value which is also the value of $F(\vec{\lambda})$ is computed. The whole calculating is a progress of affinity estimation.

3) Clone these n best individuals, and generate temporary population T(Ab). The clone size increases as the increasing of its OIF value. The quantity of clonal bodies is described as formula (5).

$$n_{clone} = round\left(\frac{\beta \times n}{i}\right) \tag{5}$$

n_{clone} is the quantity of antibodies after an antibody is cloned. β is the increment index. n is the quantity of all the antibodies in T(Ab). round() is the rounding operation. i is the antibody's index which indicates the order of the OIF value(decreasing).

4) After cloning, the next step is mutation. The purpose is to carry out the effective global search. A mutation operation is used to temporary population T(Ab), and then a mature mature population T^*(Ab) is generated. The larger OIF value, the more information the selected bands contain, and the less part the individual should be changed. The rule is shown in formula (6).

Mutation rule: Suppose that $\vec{\lambda}$ ($\vec{\lambda} = \{\lambda_1, \lambda_{2,} \ldots \lambda_N\}$)is selected to mutate. The model defines a variable ω to control the mutation. k elements(λ_i) in $\vec{\lambda}$ are chosen to change to the other wavelengths randomly. k conforms to inverse ratio with $F(\vec{\lambda})$.

$$k = round\left(\frac{\omega \times n}{n - i}\right) \tag{6}$$

ω is the mutation index. n is the quantity of all the antibodies in T^*(Ab). i is the antibody's index which indicates the order of the OIF value in T^*(Ab).

5) Select d $\vec{\lambda}s$ whose $F(\vec{\lambda})$ is max from T^*(Ab), and a set T^*_d is composed. T^*_d is an better solution set, and will be used to improve the original population.

6) Replace d worst individuals from original population S(Ab) by T^*_d, and a clonal selection of S(Ab) is completed.

7) Evaluate the original population S(Ab). If the result reach the acceptable domain, S(Ab) is the final result and the bands sets in S(Ab) are the best feature. If not, go to the step 2) and do another clonal selection on S(Ab) until the evaluate result get the given domain.

4. RESULTS AND CONCLUSIONS

After pretreatment, the experiment select 176 bands from a hyperion image data for the input data. Let the size of original population be 50, and the length of individuals be 4. The experiment is carried out in the MatLab 7.0 environment. When β is 0.631, ω is 0.873, and n is set to 10, d is set to be 8, HDRM displays fast convergence. With the increasing of the clone selection times, the average OIF value in original set S_n increases accelerated (Figure 3).

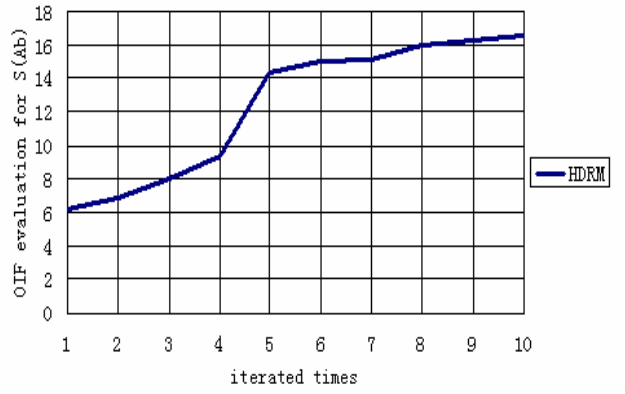

Figure 3. The evaluation result for feasible solution set in clonal selection progress

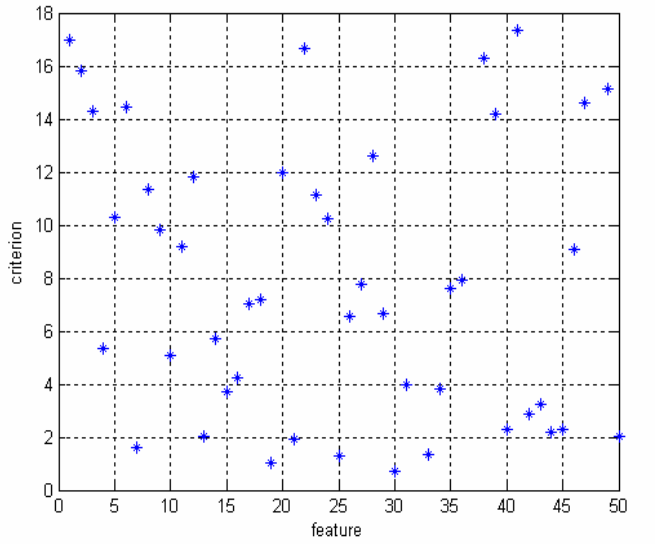

Figure 4. Criterion values in original population S($\vec{\lambda}$) set

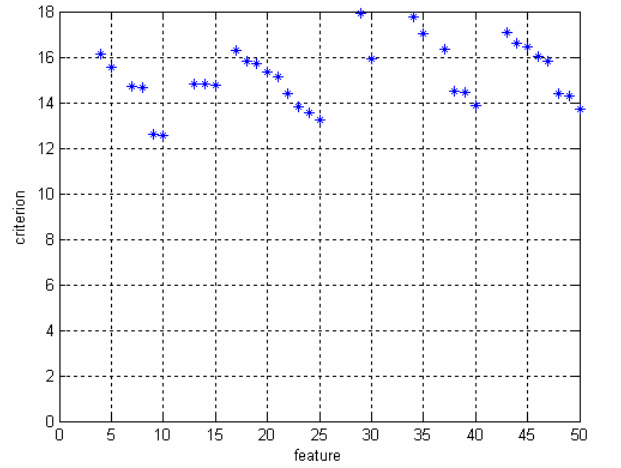

Figure 5. Criterion values in population $S(\vec{\lambda})$ set after 10 iterated times

When $S(\vec{\lambda})$ is clonal selected for 10 times, its individuals have gotten to nice convergence (Figure 4 and Figure 5). In Figure 4, the individuals are partial regular, because they were arranged during the clone selection progress.

It could help us faster solving a feature selection problem by involving the HDRM. The effect of indexes in HDRM is shown clearly during the experiment. M which is the size of the original population decides the calculating size during the progress.

β is the increment index. When it increases, the iterated times decreasing obviously, but the time calculation cost increasing much. So, it is needed to be set to an adaptable value. This paper set it 0.631 through experiment.

ω is the mutate index. If it is too larger, the random possibility increases. The information original individuals contains could be loss too much. If it is too smaller, its search will be too partial, and can not to reach the global domain.

5. FUTURE WORK

In this paper, a thought based AIS is attempted and used. It solved a simple feature selection problem. In real application, the problem may be more complex. This paper just chooses one evaluating method (or index) OIF. Generally, more evaluating methods are needed to be taken in consideration for satisfaction result. How to introduce more indexes is an unknown question needed to be explored.

The clonal rule and the mutate rule have the potential to be improve, too. Some thought from immune evolution and Generate algorithm could be referenced (Fogel, 1994). It is obvious that they can affect the efficiency of the model directly.

This research is base on the immune evolution thought in multi-objective optimization, which is widely researched. But its application in hyperspectral image is not too many so far. Some works has been done in this paper, and more works are needed to deep.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge Lv and Dr. Li for providing useful suggestion during the experiment and the pretreatment of hyperion data.

This research was supported by National High-tech R&D Program of China (863 Program) (2007AA12Z174) and National Natural Science Foundation of China (40771155).

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