AN CBRSIR FEATURES COMPRESSION APPROACH BASED ON DPSO AND SVM

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ABSTRACT:

The number of image features used by content-based remote sensing image retrieval (CBRSIR) system is not less than one hundred, and the image amount is very large, at the same time, the time cost is very important to the retrieval system. So the image feature compression is a crucial subject to CBRSIR. This paper proposed a high dimensional feature's compression approach based on discrete particle swarm optimization (DPSO) and support vector machine (SVM). This approach trained the SVM classifier by DPSO, and gained the particle's fitness by both the train data and the verification data. By iterative processing, the optimized high dimensional feature compression result achieved. This paper addressed the theory and the flow of the new approach in detail and the experiment verified the effectiveness of the new approach.

1. INTRODUCTION

With the development of computer network technology and the cost reduction of mass data storage, image database is widely used as a platform for image storage, manage and processing. At the same time, traditional retrieval methods, which are always used to retrieve text and figures, can't be used to retrieve images from image database. How to effectively retrieve images from image database becomes a problem. Consequently, content-based image retrieval (CBIR) is proposed to resolve the problem. Content-based remote sensing image retrieval (CBRSIR) is a hot and difficult research topic in the field of remote sensing image processing and management. This paper focuses on the features compression problem of CBRSIR field.

The amount of image features used by CBRSIR research is always more than one hundred, and the amount of images is usually very large. Meanwhile, the retrieval processing is expected to be finished in a relatively short time. So developing an effective image feature compression method, which can use as less features as possible to indicate as much characters of the specified remote sensing image as possible with small time cost, is a crucial subject to CBRSIR. Feature images, KLT, and clustering methods are commonly used in the feature compression field (Raymond, 1996; C. Faloutsos, 1995; G. Salton, 1982). Due to the images of the CBRSIR system are commonly refreshed frequently, the feature compression method should not self-exist without the images and the retrieval interests.

This paper proposes a high-dimension feature compression approach based on discrete particle swarm optimization (DPSO) and support vector machine (SVM).

In CBRSIR, the image features can be viewed as a vector or a point in high dimensional space, therefore, the feature compression problem in CBRSIR is a discrete optimization problem in fact.

2. METHODOLOGY

2.1 Particle Swarm Optimization and Discrete Particle Swarm Optimization

Particle swarm optimization (Kennedy, 1995; Eberhart R. C., 1995; Eberhar R. C., 1996; Kennedy, 1997) is inspired by swarm intelligence while seeking foods, and it belongs to velocity-displacement optimization methods. Particle is one solution of the solution space, corresponding to the chromosome of the artificial intelligence (Holland, 1975; Wang, 2002; Dorigo, 1999; Dorigo, 1997). If the solution space is in d-dimension, a particle can be denoted as $x=(m_1,m_2,\ldots,m_d)$. And the particle swarm is the muster of particles. If a particle swarm contains n particles, a particle swarm can be denoted as $S = \{x_1,x_2,\ldots,x_n\}$. Then, the particle swarm optimization algorithm is:

$$\begin{aligned} v_{i+1} &= v_i + c_1 \times rand_1 \times (p_i - x_i) + c_2 \times rand_2 \times (g - x_i) \\ x_{i+1} &= x_i + v_{i+1} \end{aligned} \tag{1}$$

This algorithm prompts the particles' velocity and position relationship between the i generation and i+1 generation, where v_i is the particle's velocity (prompts the position change between the consecutive generations); P_i and g are the individual optimal and global optimal, individual optimal is the optimal value of every particle, and global optimal is the optimal value of all particles in the swarm; C_1 and C_2 are the study factors, which prompts the study ability of the individual optimal and global optimal; $rand_1$ and $rand_2$ are both random numbers between [0, 1], and the study factors are always valued $C_1 = C_2 = 2$. The fitness function's purpose is scoring the fitness of the particle, and guiding the training process, and the fitness function is always determined by the optimization purpose. The particle velocity refresh is comprised of three

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parts: current velocity, the modification of the individual optimal to the velocity and the modification of the global one. Comparing with other optimization algorithms, PSO records the individual optimal and global optimal, and imports the study factors. These characters make PSO algorithm easier-understood, less-parameters, quicker-optimization and adjustable optimization step.
PSO algorithm is initially designed to resolve consecutive optimization problems. In CBRSIR region, the image features is the discrete point (high dimensional vector) in the high dimensional feature space, so the feature compression of CBRSIR belongs to discrete optimization problem.
If the dimension of the features is n while before compression process, a binary vector can be defined as following:

$$p = (f_1, f_2, ..., f_n) \tag{2}$$

Where, f_i equals to one or zero, prompts that select or deselect the i-th feature as the image feature. So, the feature compression problem converts to finding an optimal binary vector, in other words, finding an optimal binary vector from 2^n vectors.
To get the optimal compression result for specified remote sensing images and to use the compression result in the retrieval process, some “supervised” information is needed, such as some known-classification image sets. By means of the information and the SVM algorithm, the compression result can be achieved and used in the retrieval process.

2.2 Feature Compression Methodology Based on DPSO and SVM

2.2.1 Feature Compression Workflow

The proposed features compression approach converts the optimization processing to finding the optimal binary vector. Every element of the vector, indicates whether the feature can be compressed or not. The particle is a vector here, and the particle swarm is comprised by many particles. The number of the particles is decided by the size of the dataset. This approach randomly initializes particles (the binary vectors) to construct particle swarm first, divides the dataset into training data and verification data automatically. The training data is used to train the SVM classifier, and the verification data is used to verify the compression result. The fitness value is calculated based on both training data and verification data, after the SVM classifier is trained by the training data. When the velocity and position of every particle have been calculated, the fitness value of the particle is compared with the swarm’s global optimal fitness and its own optimal fitness. If a particle’s fitness value is better than them, the swarm’s global optimal fitness and the particle’s individual optimal fitness will be refreshed. And then a new round of optimization calculation resumes. If the optimal fitness or the iteration number has reached a specified threshold, the optimization processing will be finished. Otherwise, the processing will continue. By iterative processing, the high dimensional features compression result will be achieved.
Figure 1 indicates the CBRSIR feature compression flow chart based on DPSO and SVM.

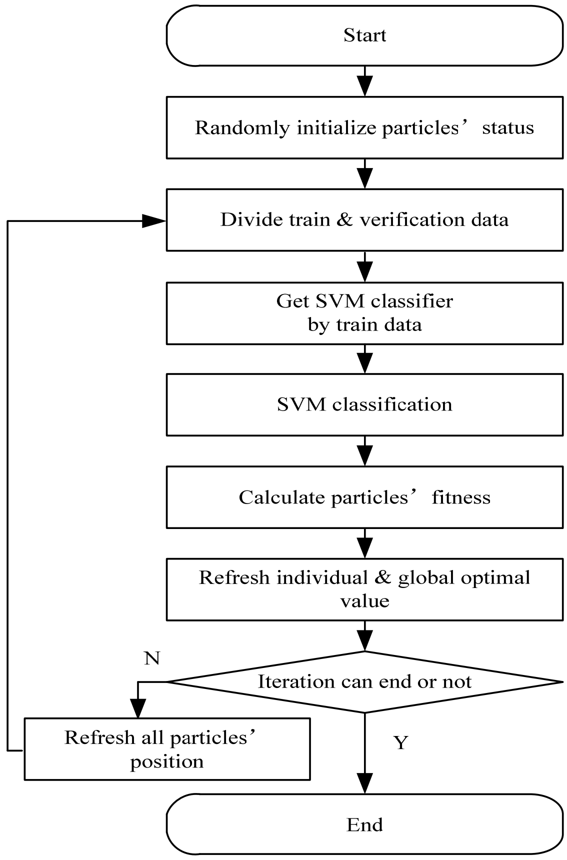


Figure 1 The flow chart of features compression based on DPSO and SVM

2.2.2 Particle’s status refresh in DPSO

Due to every particle’s vector elements is zero or one, the particle status refresh can’t directly use the consecutive formula, as (1). This paper proposed the following status refresh formula:

$$x_{i+1,d} = \begin{cases} g_{i,d}, & r \in [0,0.25) \\ p_{i,d}, & r \in [0.25,0.5) \\ r', & r \in [0.5,0.75) \\ x_{i,d}, & r \in [0.75,1] \end{cases} \tag{3}$$

Where, $g_{i,d}$ and $p_{i,d}$ are the particle’s d-th dimensional global and individual optimal value after the i times iteration process, randomly set r' one or zero, and $x_{i,d}$ indicates the particle’s d-th dimensional value in the i-th iteration process.

2.2.3 The Fitness Function

The fitness function is very important to CBRSIR features compression. This paper establishes the mathematic model of fitness function based on two principles: first, the dimension of the compressed features should be as less as possible; second, the representation of the compressed features should equal to or not far less than that of uncompressed features.
If the feature number before the compression process is D, the SVM’s classification accuracy is f, and the feature number after

the compression process is d, so the fitness should fulfill the following conditions:

If $f_1 = f_2$ and $d_1 = d_2$, then $F_1 = F_2$;
If $f_1 = f_2$ and $d_1 < d_2$, then $F_1 > F_2$;
If $f_1 > f_2$ and $d_1 < d_2$, then $F_1 > F_2$;
If $f_1 > f_2$ and $d_1 = d_2$, then $F_1 > F_2$;
If $f_1 > f_2$ and $d_1 > d_2$,
If $(f_1 - f_2)/(d_1 - d_2) \geq p$, then $F_1 > F_2$;
If $(f_1 - f_2)/(d_1 - d_2) < p$, then $F_1 < F_2$

Where $p \in R^+$, is a constant value, which is used to adjust the fitness function's two factors ratio: classification accuracy and the number of features.

Based on this mathematic model, a fitness function constructed:

$$F(f, d, D) = f - pd \tag{4}$$

2.2.4 Experiment

To verify the features compression approach based on DPSO and SVM, the IRIS dataset is chosen to test. Iris is a famous dataset in the field of pattern recognition. It is comprised by one hundred and fifty records, which belong to three kinds, setosa, versicolor and virginica, and every record contain four features, in other words, every feature is a four dimensional vector.

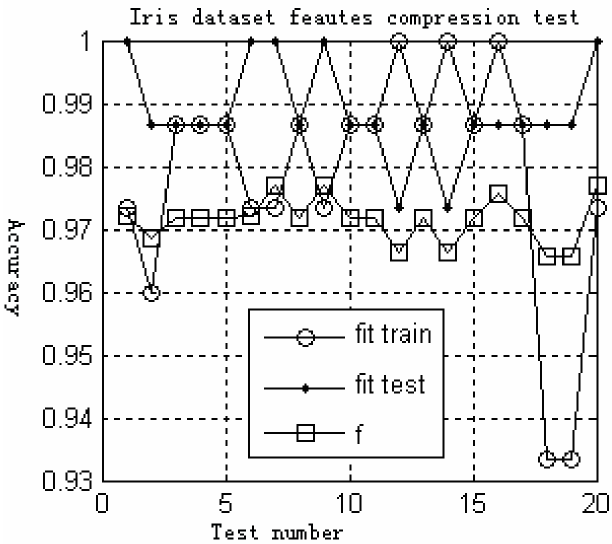
This experiment divides 150 records into train dataset and verification dataset randomly, which contain 120 records and 30 records (every kind of dataset contain 40 train records and 10 verify records). The following fitness function used in the experiment:

$$\begin{aligned} f &= 0.3 * fit\_train + 0.7 * fit\_test \\ p &= 0.005 \end{aligned} \tag{5}$$

Where *fit_train* is the classification accuracy of the train dataset, and *fit_test* is the verification dataset's classification accuracy.

In this experiment, twenty times compression test processed. Because it's random to select the train dataset and verification dataset, there're small difference between 20 tests. Figure 2 shows the test results. It's obvious that the vector '1011', corresponding decimal '11', is much more optimized. The average accuracy of verification dataset is 97.87%, the average accuracy of train dataset is 98.87%, and the average fitness is 97.14%.

Using our approach, the features can be compressed to seventy-five percent while the negative affects to expression of the record is not more than four percent. The test result indicates that the feature compression approach based on DPSO and SVM is very effective.



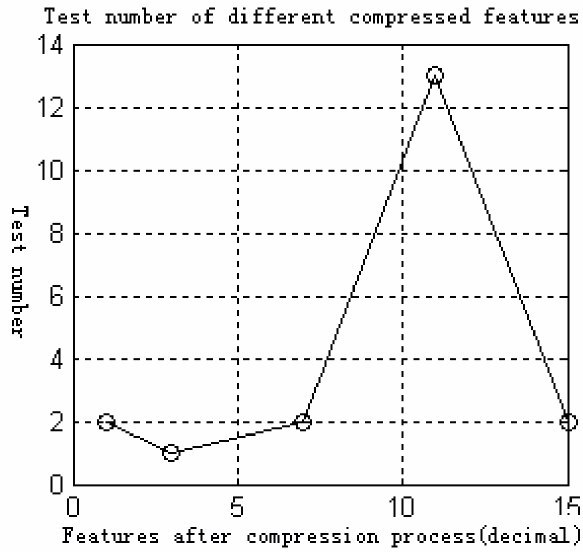


Figure 2 The experiment results of dimensions compression based on DPSO and SVM

3. CONCLUSIONS

This study covers two hotspots, content-based remote sensing image retrieval and feature compressions. Since the remote sensing images are so diverse and affected by many factors, such as sensor, filter, acquisition geometry, weather condition, spatial resolution, spectral bands, and so on, the feature compression is very necessary and important to CBRSIR. Moreover, this study using the DPSO and SVM, which are both very latest techniques, to accomplish the feature compression. Finally, the test result indicates that the approach is quite stable and effective.

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