POLSAR IMAGE CLASSIFICATION USING BP NEURAL NETWORK BASED ON QUANTUM CLONAL EVOLUTIONARY ALGORITHM

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1. INTRODUCTION

POLSAR image classification has played an active role in many aspects. It can be divided into supervised classification and unsupervised classification according to whether they need artificial guidance. Because supervised classification uses more prior knowledge, it can achieve better classification effect. Unsupervised classification needs artificial guidance and automation degree is higher.

In supervised classification methods, the most popular method is based on the Bayesian distribution of polarization data. The main ideas of this method are that the statistics distribution of scattering vector is multiple complex Gaussian distribution and the statistics distribution of covariance matrix is complex Whishart distribution. Unsupervised classification methods include two aspects. One type is based on the Polarimetric target decomposition. The other type is based on artificial intelligence algorithms such as support vector machine, clustering analysis and neural network. Recently, neural network is a popular classifier for POLSAR image. In 2003, Mohamed Yahia proposed an unsupervised classification based on neural network of which the training pixels are got by FCM algorithm [1]. In 2007, Kamran Ullah Khan and Yang Jian classified the POLSAR image using artificial neural networks based on SOM [2].

2. PROCUDURE OF BP NEURAL NETWORK CLASSIFIER BASED ON QUANTUM CLONAL EVOLUTIONARY ALGORITHM

In this paper, BP neural network based on quantum clonal evolutionary algorithm is used as a classifier for POLSAR image. More specifically, quantum clonal evolutionary algorithm (QCEA) [3] is used to optimize initial weights of BP neural network in this paper because unreasonable initial weights will result in poor convergence capability of BP neural network. We discussed this classifier as following.

Fig 1 illustrates the flowchart of whole procedure which is divided into a training phase (a) and a classification phase (b). Stage 1 of training phase is choosing training pixels. Firstly, some features are extracted and effective features are selected by single criterion algorithm based on Link-like Agent Genetic Algorithm (LAGA). LAGA is an improvement of GA. Because link-like agent structure which promotes information exchange of adjacent individuals is introduced, LAGA is more likely to converge to a optimal solution than GA. Secondly, choose training pixels based on selected features and Freeman decomposition results. Stage 2 of training phase is optimizing the initial weights of BP neural network by QCEA. Stage 3 of training phase is training the BP neural network. The weights of BP neural network are updated by gradient descent method based on deviations between the actual outputs and ideal outputs of training pixels. Fig 1 (b) shows the flowchart of classification phase. In this part, the membership of each pixel in POLSAR image is acquired by BP neural network and the classification map is got.

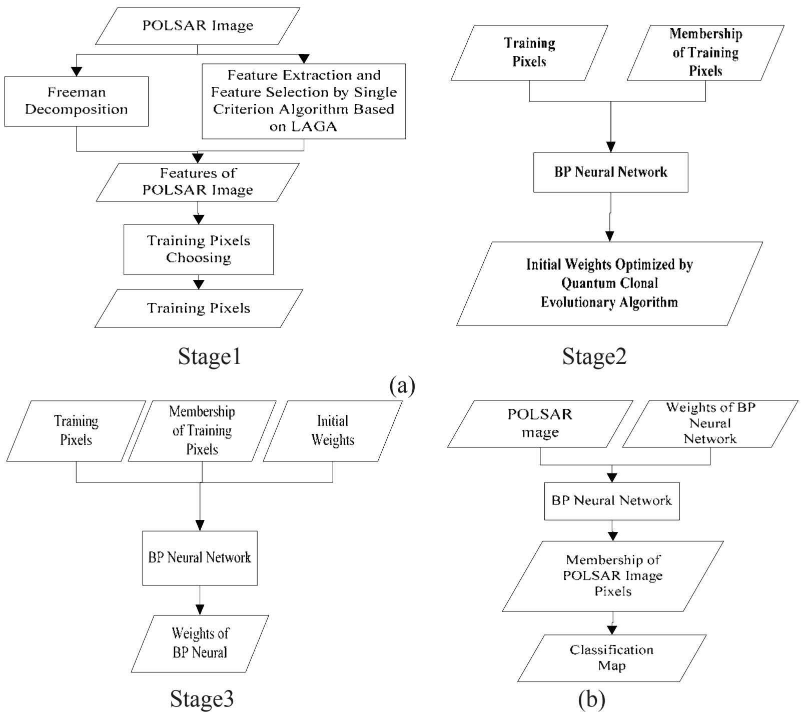

Fig 1 POLSAR Image Classification Using BP Neural Network based on Quantum Clonal Evolutionary Algorithm (a) Training Phase (b) Classification Phase

In this paper, the most important part is optimizing initial weights of BP neural network by QCEA. Section 3 illustrates the principle of QCEA and the procedure of how to optimize the initial weights.

3. OPTIMIZING INITIAL WEIGHTS OF BP NEURAL NETWORK BY QUANTUM CLONAL EVOLUTIONARY ALGORITHM

BP neural network is sensitive to initial weights because it is based on gradient descent method. Generally, initial weights are set by some empirical formulas and this may result in some problems. Because the unreasonable initial weights may result in the oscillation of the networks, the networks will not be convergent. Even if the networks are convergent, the slow speed of convergence will cost a lot of training time. Besides, the unreasonable initial weights are likely to make neural networks land in local optimal value. In order to avoid these problems, QCEA is used to optimize the optimal initial weights.

Quantum clonal evolutionary algorithm is the combination of quantum algorithm and clone operator. Therefore, QCEA has both high-speed parallel computing capability of quantum algorithm and global convergence capability of clone operator. Quantum algorithm is a high-speed parallel computing algorithm and this capability is decided by quantum coding system. In quantum coding system, the state of one quantum bit can be expressed as $|\phi\rangle = \alpha|0\rangle + \beta|1\rangle$, in which $|0\rangle,|1\rangle$ are the basic states of one classic bit and α,β which satisfy $|\alpha|^2+|\beta|^2=1$ are the possible probability of the two basic states. Therefore, one quantum bit is represented by a couple of plurals α,β . So, a system with 2 quantum bits can be expressed as: $\begin{pmatrix} \alpha_1 & \alpha_2 \\ \beta_1 & \beta_2 \end{pmatrix}$. The state of this quantum system can be expressed as: $\alpha_1 \bullet \alpha_2 |00\rangle + \alpha_1 \bullet \beta_2 |01\rangle + + \beta_1 \bullet \alpha_2 |10\rangle + \beta_1 \bullet \beta_2 |11\rangle$. We can see that this quantum system contains 4 states. If we operate to this quantum system, the 4 states are operated at the same time. Applied quantum coding to evolutionary algorithm, one chromosome length of m is encoded to one quantum system with m quantum bits. Obviously, quantum coding can accelerate the speed of evolutionary effectively. We named this chromosome quantum chromosome in this paper.

Compared to traditional GA, clone operator can converge to the global optimal solution quickly. There are three steps in clonal operator: cloning, mutation, selection. The essence of clone operator is expanding the search range of optimal individuals by clone and mutation, enriching information of the population and selecting the optimal individuals as offspring population. The three steps are discussed in detail in the description of Fig 2(a).

Fig 2(a) illustrates the procedure of quantum clonal evolutionary algorithm.

1) Initialize the population and evolutionary generation t. Population of t -th generation can be expressed as:

$$Q(t) = \left\{ q_1^t(t), q_2^t(t), \cdots, q_n^t(t) \right\} \tag{1}$$

where n is size of population, $q_j^t(t) = \begin{pmatrix} \alpha_1^t & \alpha_2^t & \cdots & \alpha_m^t \\ \beta_1^t & \beta_2^t & \cdots & \beta_m^t \end{pmatrix}$ $j = 1, 2, \cdots n$ is quantum chromosome.

2) Clone $Q(t)$ to $Q_i^{'}(t)$. The clone procedure can be described as:

$$T_c^C(Q(t)) = \left[T_c^C(q_1(t)), T_c^C(q_2(t)) \cdots T_c^C(q_n(t)) \right]^T \tag{2}$$

where $T_c^C(q_i(t)) = I_i \times q_i(t), i = 1, 2 \cdots n$, I_i is a_i -dimensional row vector, a_i is the clone size of antibody and can be calculated by $a_i = \mathrm{int}\left(N_c \times f(q_i) / \sum_{j=1}^{n} f(q_j) \right), i = 1, 2, \cdots n$. The cloned population becomes:

$$Q'(t) = \left\{ Q(t), Q_1^{'}(t), Q_2^{'}(t), \cdots, Q_n^{'}(t) \right\} \tag{3}$$

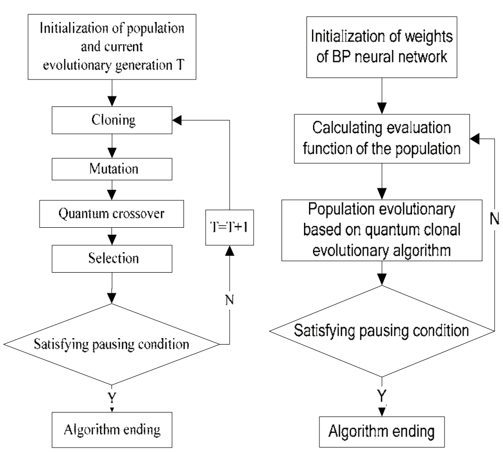

Fig 2 (a) Quantum clonal evolutionary algorithm
(b)Optimizing initial weights of BP neural network

where $Q_i^{'}(t)$ is the copy to original chromosome q_i. And the mutation and crossover is not applied in $Q(t)$.

3) The population $Q_i^{'}(t)$ mutates to $Q_i^{''}(t)$. In this paper, the Gaussian mutation is used.

4) Recombine the population $Q_i^{''}(t)$ to $Q_i^{'''}(t)$. In this paper, quantum crossover is introduced. Compared to commonly-used crossover, Quantum crossover is a recombination to all the individuals in the population.

5) Select offspring population $Q(t+1)$ from $Q_i^{'''}(t)$. In this step, for $\forall i = 1, 2, \cdots, n$, if the recombined optimal individual $b(t) = \left\{ q_{ij}(t) \,|\, \max f\left(q_{ij}^{'}(t)\right) | \, j = 1, 2, \cdots a_i - 1 \right\}$ satisfies $f(q_i(t)) < f(b(t)), q_i(t) \in Q(t)$. Then $q_i(t)$ is replaced by $b(t)$.

(6) If pausing condition is satisfied, the algorithm ends. Otherwise, the algorithm returns to (2).

Fig 2(b) shows the procedure of optimizing initial weights of BP neural network.

1) Initialize the weights of BP neural network. Generate a quantum chromosome population randomly and allocate the elements of chromosomes to the weights of BP neural network.

2) Calculate evaluation function. Generally, the reciprocal of error sum of square is used for evaluation function. The error is the difference of membership got by BP neural network and idea membership of training pixels.

3) Optimize the weights with quantum clonal evolutionary algorithm.

4) If pausing condition is satisfied, the optimal weights are acquired. Otherwise, the algorithm returns to (2).

4. EXPERIMENT RESULTS

The test image is acquired by ESAR. The feature extracted are: $10\log_{10}\left(\left\langle |s_{hh}|^2 \right\rangle\right)$, $10\log_{10}\left(\left\langle |s_{hv}|^2 \right\rangle\right)$, $10\log_{10}\left(\left\langle |s_{vv}|^2 \right\rangle\right)$, $10\log_{10}\left(\left\langle |s_{hh}s_{vv}^*|^2 \right\rangle\right)$, M , Texture based on forest, Texture based on farmland 1, Texture based on farmland 2, texture based on farmland 3, texture based on buildings, T_{11} , T_{22} T_{33} , $|T_{12}|$, $|T_{13}|$ $|T_{23}|$, $\log(T_{11}(p,q))$, $T_{11}{}^2(p,q)$. The features selected by LAGA are showed in Fig 4(c) to (n).

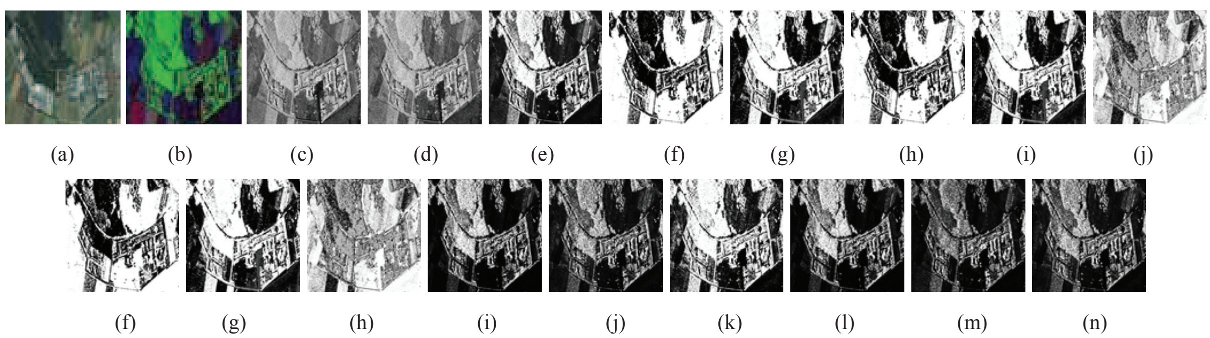

Fig. 3 (a) Optical image of ESAR (b) Freeman decomposition result (c) $10\log_{10}\left(\left\langle |s_{hh}|^2 \right\rangle\right)$ (d) $10\log_{10}\left(\left\langle |s_{hh}s_{vv}^*|^2 \right\rangle\right)$ (e) M (f) Texture based on forest (g) Texture based on farmland 1 (h) Texture based on farmland 2 (i) T_{11} (j) T_{33} (k) $|T_{12}|$ (l) $|T_{23}|$ (m) $\log(T_{11}(p,q))$ (n) $T_{11}{}^2(p,q)$

After optimal initial weights are acquired, train BP neural network to get the final optimal weights by gradient descent method. Then the trained BP neural network is used as classifier for POLSAR image. Firstly, the membership of each pixel of POLSAR image is acquired. Secondly, use different colors to represent each type of targets and get the classification map. Finally, classification accuracy of test image will be analyzed in this paper.

REFERENCES

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