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Short communication

Multiscale modeling for classification of SAR imagery using hybrid EM algorithm and genetic algorithm

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Abstract

A novel method that hybridizes genetic algorithm (GA) and expectation maximization (EM) algorithm for the classification of synthetic aperture radar (SAR) imagery is proposed by the finite Gaussian mixtures model (GMM) and multiscale autoregressive (MAR) model. This algorithm is capable of improving the global optimality and consistency of the classification performance. The experiments on the SAR images show that the proposed algorithm outperforms the standard EM method significantly in classification accuracy.

Keywords: SAR imagery; Classification; Multiscale; Hybrid EM algorithm; Genetic algorithm

1. Introduction

In recent years, synthetic aperture radar (SAR) imaging has been rapidly gaining prominence in applications such as remote sensing, surface surveillance, and automatic target recognition. For these applications, the classification of various categories of clutter is quite important and it can play a key role in the subsequent analysis for target detection, recognition and image compression. Because of the nature of the SAR instrument, SAR images contain speckle noise, complicating their classification. Several different classification methods especially designed for SAR data have been proposed. Recently, different multiresolution classification algorithms, such as the multiscale autoregressive (MAR) model, have been proposed [1–3]. Because imagery data of each class must be known for the method using the MAR model, a new multiscale unsupervised classification method is proposed using the expectation maximization (EM) algorithm [4]. However, those EM algorithms converge to a local optimum and the result is sensitive to initialization. To alleviate these problems, this paper presents a framework that hybridizes the genetic algorithm (GA) and the EM algorithm (HGAEM) for the classification of SAR images based on the MAR model and finite Gaussian mixture model (GMM). The GA is a robust, global optimization algorithm that is capable of finding the global optimum in a multi-modal search space. The hybrid algorithm achieves better classification by using GA to select the optimal subset of data to be the initial cluster centers and a local-learning method to locally optimize the GA-selected initial centers. The likelihoods of the optimized solution are used as the objective function for GA. This framework exploits both the global exploratory property of GA and the efficiency of the local-learning method.

This paper is organized as follows. In Section 2, quadtree interpretation of SAR imagery and its multiscale autoregressive model are given. In Section 3, the hybrid classification algorithm of SAR image is proposed. Some

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experimental results are shown in Section 4. Finally, we draw the conclusions.

2. Quadtree interpretation of SAR imagery and its MAR model

2.1. Multiscale sequence of SAR image

The starting point for our model development is a multiscale sequence $X_L, X_{L-1}, \ldots, X_0$ of SAR images, where X_L and X_0 correspond to the coarsest and finest resolution images, respectively. The resolution varies dyadically between images at successive scales. More precisely, we assume that the finest scale image X_0 has a resolution of $\delta \times \delta$ and consists of an $N \times N$ array of pixels (with $N = 2^M$ for some M). Hence, each coarser resolution image X_m has $2^{-m}N \times 2^{-m}N$ pixels and $2^m\delta \times 2^m\delta$ resolution. Each pixel $X_m(k, l)$ is obtained by taking the coherent sum of complex fine-scale imagery over $2^m \times 2^m$ blocks, performing log-detection (computing 20 times the log-magnitude) and correcting for zero frequency gain variations by subtracting the mean value. Accordingly, each pixel in image X_m corresponds to four "child" pixels in image X_{m-1}. This indicates that quadtree is natural for mapping. Each node s on the tree is associated with one of the pixels $X_m(k, l)$ corresponding to pixel (k, l) of the SAR image X_m. For example, Fig. 1 illustrates a multiscale sequence of three SAR images, together with the quadtree mapping. Here, the finest-scale SAR imagery is mapped to the finest level of the tree, and each coarse scale representation is mapped to successively higher levels. We use the notation $X(s)$ to indicate the pixel mapped to node s. The scale of node s is denoted by $m(s)$.

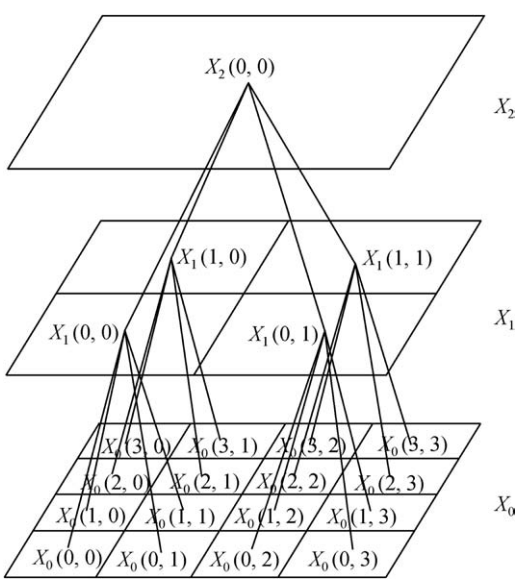

Fig. 1. Sequence of three multiresolution SAR images mapped onto a quadtree.

2.2. Extraction and modeling of multiscale statistical character of SAR image

Considering the multiscale sequence of SAR imagery, we choose a specific class of multiscale models, named multiscale autoregressive models as follows:

$$x(s) = a_1 x(s\bar{\gamma}) + \cdots + a_p x(s\bar{\gamma}^p) + \omega(s) \tag{1}$$

where $a_1, \ldots, a_p$ are autoregressive coefficients, $\omega(s)$ is noise, $X(s\bar{\gamma})$ is parent nodes of $X(s)$, and p is the order of regression. For the application of segmenting different types of clutter in SAR imagery, a MAR model can be constructed for each clutter class and for each scale. The coefficients are decided by least square estimation, and the model order p may be selected in the manner similar to that by which standard autoregressive model orders are chosen for each scale. The same coefficients apply to all pixels on the same scale, but the coefficients for different scales need not be the same. The multiscale statistical characterization $t(s) = (a_{1,s}, a_{2,s}, \ldots, a_{p,s})$ of SAR image is obtained for all the nodes and scales.

For multiscale statistical character $t(s)$, we model them using the Gaussian mixture model [5], that is

$$p(t(s)|\Theta) = \sum_{k=1}^{K} \pi_k \varphi(t(s)|\mu_k, \Sigma_k) \tag{2}$$

where $\phi(.)$ is the probability density function of a standard normal distribution. K is the number of classes, and $\Theta = \{\pi_i, \mu_i, \Sigma_i | i = 1, 2, \ldots, M\}$, $\sum_{k=1}^{K} \pi_k = 1$, $\pi_k > 0$.

Let $Z(s) = (Z_1(s), \ldots, Z_K(s))$ be the classification membership vector for the sth pixel where $Z_k(s) = 1$ if the sth pixel belongs to the kth classification and 0 otherwise. The standard method for GMD learning is to treat $Z(s)$ as missing variables and apply the EM algorithm. The EM algorithm performs parameter estimation through maximizing the complete data log likelihood $L_c(\Theta)$ given by

$$\log L_c(\Theta) = \sum_{m(s)=l} \sum_{k=1}^{K} z_k(s)\{\log \pi_k + \log(\varphi(t(s)|\mu_k, \Sigma_k))\} \tag{3}$$

The maximization is achieved by EM algorithm. That is iterating (4)–(7),

$$\tau_j^{(t+1)} = \frac{\pi_j^{(t)} \varphi\left(t(s)|\mu_j^{(t)}, \Sigma_j^{(t)}\right)}{\sum_{k=1}^{K} \pi_k^{(t)} \varphi\left(t(s)|\mu_j^{(t)}, \Sigma_j^{(t)}\right)} \tag{4}$$

$$\tau_j^{(t+1)} = N^{-2} \sum_{m(s)=l} \tau_j^{(t)} \tag{5}$$

$$\mu_k^{(t+1)} = \sum_{m(s)=l} \tau_j^{(t)} y(s) \Big/ \sum_{m(s)=l} \tau_j^{(t)} \tag{6}$$

$$\sum_{k}^{(t+1)} = \sum_{m(s)=l} \tau_j^{(t)} \left(y(s) - \mu_j^{(t+1)}\right)\left(y(s) - \mu_j^{(t+1)}\right)^T \Big/ \sum_{m(s)=l} \tau_j^{(t)} \tag{7}$$

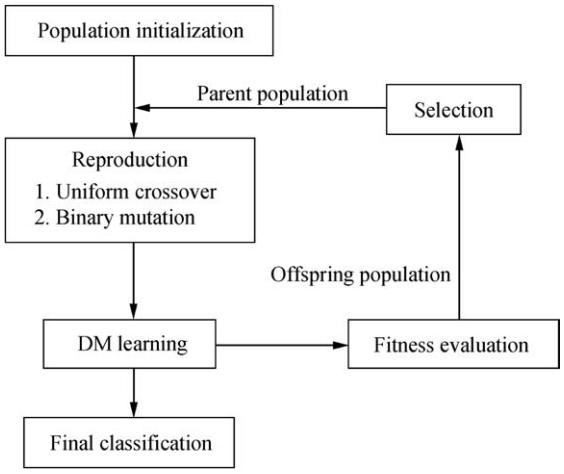

Fig. 2. The hybrid classification algorithm.

3. The hybrid classification algorithm of SAR image

The objective of the hybrid algorithm is to combine the strengths of GA and EM to produce a yet efficient classification algorithm for SAR image. The hybrid algorithm consists of two steps, as depicted in Fig. 2. In the first step, the GA searches for the optimal subset of SAR image to be the initial classification centers. In the other step, the local-learning method (EM) performs the local classification of these initial centers. The implementations of GA and EM at these levels are described as follows.

In the implementation of GA, let $N \times N$ denote the total number of pixels of the SAR image and K denote the number of classification. In GA, each solution is encoded as an $N \times N$-bit string with the ith bit position corresponding to the ith pixel for $i = [1, 2, \ldots, N \times N]$. A "1" in the ith bit position indicates that the ith pixel is selected and a "0" indicates otherwise. Thus, in order to select K optimal pixels as the initial centers, all feasible solutions must have K number of "1"s and $N \times N - K$ number of "0"s. The genetic operators include uniform crossover and mutation. Uniform crossover selects two random parents and at the crossover probability p_c, swaps the bits between the parents at the same bit position with 40% probability to create two new solutions, of which one is taken as the offspring solution. The crossover operator has the important function of passing on high fitness "schema" from the parents to the offspring. Uniform crossover has the advantage over traditional K-point crossover; in that it eliminates biases in the crossover search. Mutation simply inverts each bit of the offspring at the mutation probability p_m to diversify the search. It has the important function of preventing premature convergence. Finally, a repair operator is applied to the final offspring to ensure that the offspring is a feasible solution, i.e. it has K number of "1"s. If the solution has more than K number of "1"s, then one of the "1"s is randomly inverted, whereas if it has less than K number of "1"s, one of the "0"s is randomly inverted. The repair operator iterates until the solution has exactly K number of "1"s.

After the offspring solutions are created, they are translated into the initial conditions for the mixture models. The models are then EM optimized, and the maximum log likelihood values of the models given in (3) become the fitness of the corresponding offspring solutions. For the selection operator, we use the elitist scheme $(\mu + \lambda)$ instead of the roulette wheel to achieve faster convergence. The $(\mu + \lambda)$ operator selects the best-fit μ solutions out of the joint pool of μ parents and λ offsprings to be the next generation parents, always keeping the best solutions in the population. This whole process reiterates until some stopping criteria are reached. Over the entire process, the search not only uses stochastic genetic operations to create new search

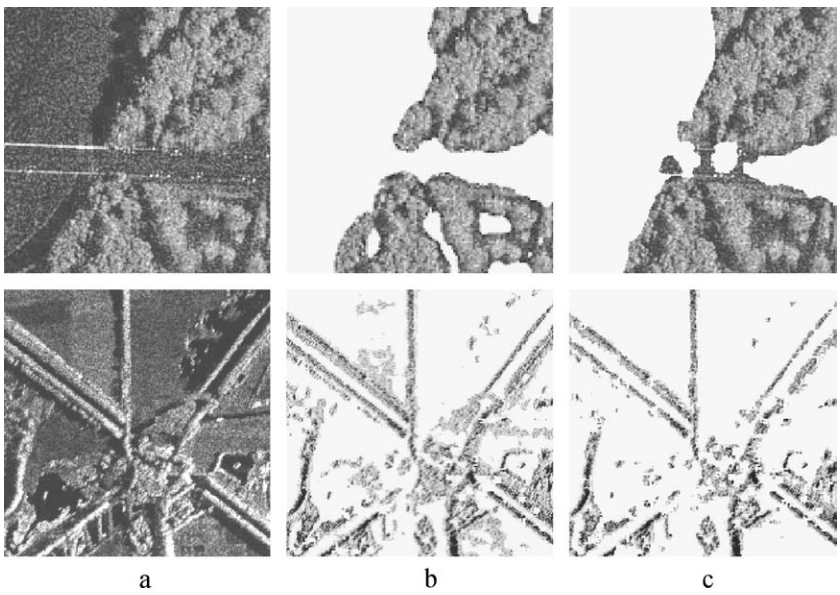

Fig. 3. (a) Original SAR image. (b) Segmented image from EM algorithm. (c) Segmented image from HGAEM algorithm.

Table 1
The percentage of pixels that are correctly segmented using EM algorithm and HGAEM algorithm.

	EM	HGAEM
Fig. 3 (top)	80	94
Fig. 3 (bottom)	75	92

points (offspring population), but also relies only on the population information and not on any gradient information. GA is therefore less susceptible to getting trapped in local optima in the multi-modal search space.

4. Experimental results for SAR imagery

To demonstrate the classification performance of our proposed algorithm, we apply it to two complex SAR images which are of size 200×200 pixel resolution (see Fig. 3(a)). From the complex images, we generate the above-mentioned quadtree representation consisting of $L = 3$ levels and use a second-order regression. The number K of Gaussian components in images is assumed to be known for the EM algorithm. The settings for GA and EM are as follows. The binary coded solution is $N \times N = 200 \times 200$ bits long with "1"s at the selected gene and "0"s at the rest. The population sizes are $\mu = 100$ for the parents and $\lambda = 200$ for the offspring. Although these population sizes are relatively small in order to shorten the computational time, they have shown to be sufficient in our experiments. The selection scheme is the elitist scheme ($\mu + \lambda$) that always keeps the best individuals in the population to accelerate convergence. Uniform crossover is applied at a high crossover rate $p_c = 0.9$, which is a common choice to facilitate transmission of optimal schema in the population. While binary mutation is often applied at the mutation rate $p_m = 1/N^2$ that yields an average of one inversion per string, we set p_m to a relatively higher rate of $p_m = K/N^2$ to yield an average of K inversions per string to increase the diversity of the search. Each GA runs for 200 generations. For EM, the weight of each component π_i is selected randomly, and the stopping criterion is when the maximum log likelihood value increases by less than 1.

Fig. 3 shows the results of applying HGAEM approach to two SAR images (Fig. 3(c)), as well as the results using EM algorithm for comparison (Fig. 3(b)). Table 1 presents the percentage of pixels (%) that are correctly segmented using the EM algorithm and HGAEM algorithm. The results we obtained show that the HGAEM slightly outperforms the EM algorithm.

5. Conclusions

The paper introduces a novel classification method based on the hybridization of GA and EM algorithm. The hybrid method is applied to the clustering of SAR image using the finite Gaussian mixture model and multiscale autoregressive model. The experimental results show the advantages of the HGAEM approach in achieving better classification, when compared with the standard approach of using random initialization EM algorithm only. The proposed hybrid GA framework can be easily extended to incorporate other local clustering methods, for example, the K-means. More globally optimal classification can be obtained by using GA for optimizing the initial conditions.

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