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Modified genetic algorithm-based sub-pixel mapping

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ABSTRACT

Sub-pixel mapping (SPM) is a promising way to predict the location of endmembers within mixed pixels at the sub pixel level. SPSAM is a real time processing algorithm for SPM, but it will generate a lot of isolated sub pixels because land cover classes were assigned to sub pixels in order. In this letter, a novel method is proposed to realize SPM. It contains two main steps: sub-pixel/pixel spatial attraction model (SPSAM) is first used to generate the initial SPM result; and then modified genetic algorithm (MGA) is applied as the post-processing method to obtain more accurate results. Three different sets of data are used for experiments: simple artificial images and two sets of real remote sensing images. The results show MGA/SPSAM outperforms the conventional SPM methods.

1. Introduction

Due to the constant increase of spectral resolution, hyperspectral remote sensing image has been widely used in many fields (e.g., agriculture, archeology, medicine, natural disaster monitoring, environmental monitoring and military field). However, its spatial resolution is still not enough to describe the spatial distribution of each land cover although it contains abundant spectral information. Mixed pixels widely exist in hyperspectral images, which have brought great difficulty in visual inspection and post-applications [1]. To solve these problems caused by mixed pixels, endmember extraction techniques are usually used to extract endmembers which only contain the spectrum information of one land-cover class [2], spectral unmixing techniques are then used to confirm the proportion occupied by each class in mixed pixels [3], and sub-pixel mapping (SPM) or super resolution mapping (SRM) are allocated each land cover class to sub-pixels based on the fraction images [4].

In recent years, sub-pixel mapping (SPM) has received considerable attention in hyperspectral remote sensing area. More algorithms are proposed to solve the problems caused by mixed pixels. Atkinson [4] presented the concept of sub-pixel mapping (SPM), which divides a mixed pixel into some sub-pixels and allocates land cover class to these sub-pixels. Here, at a sub-pixel level, there is only one land cover class. The purpose of SPM is to maximize the spatial dependence, and recently, some models are proposed for this. Verhoeye and De Wulf [5] proposed linear optimization techniques to maximize the spatial dependence. Teerasit Kasetkasem [6] adopted Markov random field (MRF) that the distribution of the center pixels is only related to the neighboring pixels. Tatem [7] and Mertens [8] used a Hopfield neural network to realize multiple-class land-cover mapping at the sub-pixel scale. Zhang [9] presented an approach based on a supervised back-propagation (BP) neural network. Boucher [10] introduced indicator geostatistics to implement SPM. Mertens [11] introduced intelligence algorithm to realize SPM. Mertens [12] applied a sub-pixel/pixel spatial attraction model which calculate the attraction of every sub-pixel in the center coarse resolution pixel and allocate the land-cover class to the sub-pixels directly. Wang [13] presented the mixed spatial attraction model for sub-pixel mapping which integrates the spatial attractions both within pixels and between them.

The purpose of SPM is to maximize the spatial dependence in the H-resolution case, which is expressed by neighborhood pixels attracting sub-pixels in center coarse pixel in SPSAM. SPSAM directly allocates land-cover classes to sub-pixels based on attractions. The advantage of this model is that it fits for real-time processing, but it cannot deal with complicated problems, such as large scale factor, which can generate a lot of isolated pixels. SPSAM only guarantee the first assigned land cover class which has the largest spatial dependence regardless of spatial dependence of the other land cover classes. To solve this problem, genetic algorithm (GA) is utilized as the post-processing, which can reduce isolated pixels and increase spatial dependence at a cost of time consumption. To solve this problem, in this letter, modified crossover operator is used to improve the efficiency of genetic algorithm.

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The rest of this letter is organized as follows. In Section 2, the proposed algorithm is presented, along with correlative techniques used in this paper, which are spatial dependence (SD), SPSAM, Modified Crossover Operator (MCA). The experiments are then carried out to validate the accuracy of the proposed model in Section 3. Finally, conclusions are drawn in Section 4.

2. Methodology

2.1. Spatial dependence

The distribution of land-cover classes is not stochastic, which has a certain spatial correlation among them. The tendency of spatially proximate observations of a given property to be more alike than more distant observation (Atkinson, 1997 [4]). The purpose of sub-pixel mapping (SPM) is to maximal the spatial dependence in H-resolution case.

The mathematic expression of spatial dependence of whole image is followed by Eq. (1):

$$SD_R = \sum_R \sum_{i=1}^{S} \sum_{j=1}^{S} \sum_{c=1}^{C} x_{ij,c} \times SD_{ij,c} \tag{1}$$

$$x_{ij,c} = \begin{cases} 1 & \text{if sub-pixel } p_{ij} \text{ is assigned to land cover class} c \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where S is the scale factor, C is the number of land cover classes, and $SD_{ij,c}$ is spatial dependence of sub-pixel p_{ij} which belongs to land-cover class c, and expressed by the neighborhood of sub-pixel p_{ij} attracting the sub-pixel p_{ij}. $SD_{ij,c}$ is calculated as followed:

$$SD_{ij,c} = \sum_{n=1}^{N} X_c(p_{ij}, p_n) \times w(p_{ij}, p_n) \tag{3}$$

$$X_c(p_{ij}, p_n) = \begin{cases} 1 & \text{if neighboring pixel } p_n \text{ is assigned to land cover class } c \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where N is the number of neighborhood pixels (in this paper, N is set to 8. That is to say, we apply a 3×3 window to calculate spatial dependence), and weight $w(p_{ij}, p_n)$ is the attraction between sub-pixel p_{ij} and p_n, and it can be calculated as the inverse of the distance between the sub-pixel p_{ij} and neighboring sub-pixel p_n or exponential distance decay model, presented in Eqs. (5)–(6):

$$w(p_{ij}, p_n) = d(p_{ij}, p_n)^{-1} \tag{5}$$

$$w(p_{ij}, p_n) = \frac{1}{W} \exp\left(\frac{-d(p_{ij}, p_n)}{w} \right) \tag{6}$$

The purpose of sub-pixel mapping (SPM) is to maximal SD_R in H-resolution case, and we apply the Modified Genetic Algorithm (MGA) to search the optimal SPM results.

2.2. SPSAM

Mertens [12] proposed a mathematic model (SPSAM) to implement SPM. In this model, the spatial dependence is expressed by a neighborhood of the coarse resolution pixel attracting sub-pixels. In this paper, SPSAM is used to generate the initial SPM result. Suppose $f_c(P_k)$ is the proportion of land-cover class (c = 1,2,. . .,C) in coarse resolution neighboring pixel P_k, and $F_c(P_k)$ is the attraction generated by neighboring pixel P_k, $F_c(p_{i,j})$ is the attraction of sub-pixel $p_{i,j}$ which belongs to land cover class c generated by all neighboring pixels. The attraction of sub-pixel $p_{i,j}$ is calculated by Eqs (7)–(9):

$$F_c(P_k) = \frac{f_c(P_k)}{{d_k}^2} \tag{7}$$

where d_k is the distance between neighboring pixel P_k and sub pixel $p_{i,j}$, which is used here to measure spatial attraction, and calculated as followed:

$$d_k = \sqrt{(x_{i,j} - X_k)^2 + (y_{i,j} - Y_k)^2} \tag{8}$$

Obviously, d_k is the Euclidean distance between geometric center of sub-pixel $p_{i,j}$ and its neighboring pixel P_k.

$$F_c(p_{i,j}) = \sum_{k=1}^{N} F_c(P_k) \tag{9}$$

N is the number of neighborhood pixels (in this paper, N = 8).

When $F_c(p_{i,j})$ (i,j = 1,2,. . .,S, c = 1,2,. . .,C) were calculated, we should decide which kind of land-cover class allocated first. After this problem settled, we could follow this principle: sub-pixels with highest attractions are assigned first (Mertens et al. 2006). SPSAM allocate land-cover classes to these sub-pixels directly which fits for real-time processing. However, it will also generate some isolate pixels. There are two reasons: Firstly, not all of sub-pixels are homogeneous distributed in the center of the neighboring pixel, and as a result, d_k is an approximate value. Secondly, the attractions between two neighboring sub-pixels have very small difference. Genetic Algorithm (GA) can solve this using Crossover Operator.

2.3. MGA/SPSAM

SPSAM only can guarantee the first assigned land cover class has the maximal spatial dependence, while other land cover classes are not. It appears that SPSAM is not the precise way to implement SPM especially in large scale situation.

Genetic algorithms (GA) are searching and optimization algorithms based on natural selection and natural genetics. It contains three steps, which are selection, crossover and mutation. Selection Operator selects the best individuals in population to replace the inferior individuals (we set the selection ratio β = 0.1), and it can increase the spatial dependence of whole population. Crossover operator is a GA operator which can create new individuals through swapping the genes between two individuals. Mutation operator is not allowed in SPM because the constraint of fraction images.

Crossover operator allows exchange of genes between two individuals. If the exchanged genes from two individuals were the same, Crossover Operator has no contribution to the fitness of individual. Some changes are made to solve this problem. Firstly, swap two genes in an individual for simplicity. Then, carry out the modified crossover operator (MCA) using the following steps, which can increase the efficiency of evolution.

Step 1: Use Eq. (3) to calculate the attraction and save it in the matrix $Attraction_0$ if $p_{i,j}$ belongs to land cover class 0, otherwise save it in the matrix$Attraction_1$ if $p_{i,j}$ belongs to land-cover class 1. In this paper we set N = 8.

Step 2: Find minimum attraction and remember their location.

Step 3: Exchange sub-pixel values at two different locations if attractiveness of the whole mixed pixel is increased.

In this letter, MGA combined with SPSAM allocate the land cover classes to sub-pixels. This whole algorithm is divided into two steps:

Step 1: SPSAM

SPSAM is used to generate the initial SPM result. SPSAM distributes the land-cover classes to the sub-pixels directly, which fits for real-time processing. But it also can generate some isolated sub-pixels. For that reason, for which step 2 is followed.