DECOMPOSITION OF OPTICAL IMAGES MIXED PIXELS BASED ON LAGRANGIAN CONSTRAINED ALGORITHM

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Mixed pixel which is commonly found in all types of remote sensing images, has been one of the key factors of the remote sensing image classification accuracy, specially for the region with complex ground distribution[1] . There are two main types of spectrum mixed pixel model, which are linear spectrum mix model[2] and the non- linear spectrum mix model[3] . Linear spectrum mix model is the most popular, but all methods have their own flaws. Aiming at the characteristic that the number of mixed pixels takes a large proportion in remote sensing images，we propose a method which is used to decompose mixed pixels based on lagrangian constrained neural network[4-8]，and propose systemic solving methods.

For resolving the problem that optical remote sensing images exist lots of mixed pixels, combining the demonstration of specific theorem in relevant content, we propose the Lagrange constrained decomposition algorithm which is used to the mixed pixels' decomposition. Adding Lagrangian constrained condition to the traditional non-bound neural network，we achieve Lagrangian constrained decomposition algorithm. The Lagrangian constrained decomposition algorithm makes more suitable for mixed pixels' decomposition model. At the same time, we improve the initialization way of mixed matrix A, which is built by using the priori relationship of X and A. The improved initialization way depresses the error which is caused by A's artificial calculation in the traditional method. The real images are intercepted from Tiananmen of Beijing as our experiment's data source .Experimental results show that the Lagrangian constrained decomposition algorithm can get significantly more precise results than others neural network which does not contain the restrictive conditions (the paper uses BP neural network as an example).

We get the objective function of each pixel:

$$L(S,A) = -\sum_{i=1}^{n} s_i ln(s_i) - \sum_{j=1}^{m} \lambda_j (\sum_{i=1}^{n} a_{ji} s_i - x_j) - (\lambda_0 - 1)(\sum_{i=1}^{n} s_i - 1))$$

The first item of the formula is the entropy of original signals, and the last two items are the constrained conditions, and $\lambda_0, \lambda_1, \ldots, \lambda_m$ are the Lagrange multipliers. The objective function L is a combined objective function which combines supervised learning with unsupervised learning. Our target is to maximize the objective function. When the objective function reaches its maximum, the entropy reaches its maximum, but the error item reaches its minimum. Therefore, the entropy and the error function are unified into the framework of the same objective function, and S is measured by maximizing the entropy, but A is measured by minimizing the error. Through the gradient method, we can get the coefficient of mixed matrix A and Vector λ. Vector S is derived by making the partial derivative of objective function 0. The iterative algorithm can help us to get vector S of each pixel.

To compare the capability of the Lagrangian constrained decomposition algorithm with the capability of non- constrained neural network. In the experiment we use the three bands remote sensing images of Beijing as the original image, and intercept 512*512 images as the Fig 1 shows. The images contain three sorts of ground features: roads/grounds 、buildings and water. Fig.2 shows the decomposition results of the Lagrangian constrained decomposition algorithm. In order to further illustrate the effectiveness of our algorithm, we Randomly selected 25, 50, 75, 100, 125, 150,175,200 pixels, record the decomposition results of our algorithm and BP neural network, and read out the corresponding geographical coordinates of these pixels from the ENVIEW, then read out the corresponding true ground of these geographical coordinates from the actual data and quantitatively measure the decomposition accuracy. Fig.3 shows the decomposition accuracy of different total number of sample points.

Fig.1 The original remote sensing image

（a） （b） （c）

Fig.2 The decomposition results of the Lagrangian constrained decomposition algorithm
Fig.2a The result of our algorithm -- water map
Fig.2b The result of our algorithm --artificial buildings map
Fig.2c The result of our algorithm -- vegetation/roads map

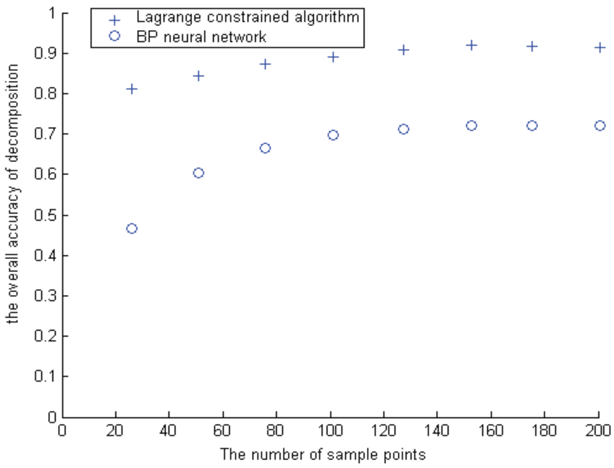

Fig.3 The decomposition accuracy of different total number of sample points

We propose the Lagrangian constrained decomposition algorithm which is used to decompose remote sensing images' mixed pixels, and give a concrete realization process of the Lagrangian constrained decomposition algorithm. We select Tiananmen of Beijing as the experimental data. The results qualitatively and quantitatively show our algorithm had a better decomposition precision and visual decomposition effect. The method has important theoretical and practical significance in solving the high-precision ground classification, target detection and identification ect.

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