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A Remote Sensing Image Classification Method Based on Evidence Theory and Neural Networks

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Abstract

Neural networks have been widely used in remote sensing image classification. In this paper, we exploited the spatial information of the image to decide the classification result and proposed a remote sensing image classification method based on D-S evidence theory and neural networks. First, the original image to be classified is smoothed with the smoothed image obtained. Next, a B-P neural network is used to train and classify the original image and its smoothed image separately. Next, the two classification results (decisions) of the B-P neural network are fused with evidence theory. Finally, the fused result is as the final classification result of the original image. Experiment results show that the new method is efficient and improves the classification accuracy largely.

1. Introduction

The automatic classification technique of remote sensing images is a branch of pattern recognition techniques in remote sensing field and has an extensive use in military and civilian areas [1]. Its aim is to identify remote sensing images, i.e. to recognize and classify ground cover information in remote sensing images thereby distinguishing the corresponding ground truth and extracting the required information [2].

Artificial neural networks have been widely used in pattern recognition area and also largely used for the classification of remote sensing images in recent years [4]. Neural networks have the properties of parallel processing ability, adaptive capability for multispectral images, good generalization and not requiring the prior knowledge of the probability distribution of the data, so when compared with statistical classification methods, neural network methods show huge superiority. Early neural network methods for classifying remote sensing images are on the basis of pixel-by-pixel, i.e. judging which class a certain pixel belongs to only according to the pixel's single value but not considering its neighbors [5][6]. Plenty of classification practice shows that there exist the phenomena of "same spectrum with different land matters" universally because of complexities of terrain and object. So the classification method only using a pixel's single value usually cannot obtain the desired result [7]. Because of the successiveness of the distribution of ground cover, in remote sensing images, there is certain correlation between neighboring pixels and a pixel's neighbors can provide useful spatial information for classification [8]. Therefore, many researchers applied the spatial information to the classification methods based on neural networks and at present, in general algorithms, a pixel's $N \times N$ neighbors are first obtained and then each pixel value in the range is as the inputs of networks. H.Bischof and some others classified remote sensing images with N=9 and their classification result is much better than that obtained using a single pixel value as input but at the cost of quantities of computation. According to statistical data, computation times increase exponentially with the number of neuron increasing, so above method slow the training speed of neural networks greatly at the same time then it improves classification precision.

In order to utilize the spatial information to improve classification effects and precision and accelerate the training speed of neural network at the same time, the paper proposed a remote sensing image classification method based on evidence theory and neural networks. First, the original image is smoothed with the smoothed image obtained. Because there exists spatial correlation between neighbor pixels of remote sensing images, the smoothed image contains the spatial information of the original image. Next, the original image and the smoothed image are trained and classified respectively by the neural network with two classification results (decisions) produced. Next, to improve classification accuracy, reliability and robustness, the two classification results are regarded as two pieces of evidence and fused with D-S evidence reasoning method [11][12]. Finally, the fused result (decision) is the final classification result of the original image. Experimental results and performance comparison show that the new method is effective and increases the classification precision greatly.

2. BP neural network

BP neural network is one of the most investigated and widely used forward feedback neural networks. In this paper, we adopted a BP neural network with one hidden layer[9].

2.1.the structure of a multiplayer BP neural network

The structure of a BP neural network with one hidden layer is showed as fig 1. The network is divided as three layers: i denotes the node of the input layer, j denotes the node of the hidden layer and k denotes the node of the output layer.

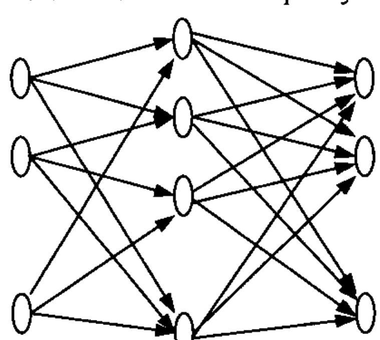


Fig.1 structure of a BP neural network with one hidden layer

2.2 the learning algorithm of a BP neural network

The BP learning error function is defined as:

$$E = \frac{1}{2}\sum_k (d_k - y_k)^2 \qquad (1)$$

where, d_k denotes the desired output and y_k denotes the actual output. Then the iterative weights updating rules are as follows:

1) for the weights between the hidden layer and the output layer:

$$w_{jk}(t+1) = w_{jk}(t) + \eta\delta_k y_j$$
$$\delta_k = y_k(1-y_k)(d_k - y_k) \qquad (2)$$

2) for the weights between the input layer and the hidden layer:

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_j y_i$$
$$\delta_j = y_j(1-y_j)\sum_k \delta_k w_{jk} \qquad (3)$$

where η is the learning rate , δ_k and δ_j are the error term.

3. A remote sensing image classification method based on evidence theory and neural network

3.1 D-S evidence theory

Evidence theory is a reasoning method dealing with uncertainty problems. In recent years it has acquired great development and is attracting more and more attention. Evidential reasoning is first proposed by Dempster in early 1967 and he calculated out the upper bound and the lower bounds of probability by multivalued mappings[11]. Then in 1976, Shafter extended and established evidence reasoning, so evidence theory is also called D-S theory.

D-S evidence theory is established on a non empty set Θ, where, Θ is called a frame of discernment and consists of an exhaustive set of elements mutually excluding. Any supposition A in question should belong to the power set of $\Theta : 2^\Theta = \{A | A \subseteq \Theta\}$. A basic probability assignment function (BPAF) is a function $m : 2^\Theta \to [0,1]$ which satisfies the following conditions:

$$m(\Phi) = 0 \qquad (4a)$$

$$\sum_{A\subset\Theta} m(A) = 1 \qquad (4b)$$

$m(A)$ is a measure of belief attributed exactly to the A and to none of the proper subsets of the A. Φ denotes the empty set. The elements of Θ that have a non zero mass are called focal elements and the union of all focal elements is called the core of the m-function. Evidence is composed of a body of evidence (A , $m(A)$) and given a body of evidence, a belief function Bel and a plausibility function Pl in the set 2^Θ are defined as [11][12]:

$$Bel(A) = \sum_{B\subset A} m(B) \qquad \forall A \subset \Theta \qquad (5)$$

$$Pl(A) = 1 - Bel(A^C) \qquad \forall A \subset \Theta \qquad (6)$$

$Bel(A)$ measures the total belief that the object is in A and $Pl(A)$ measure the total belief that can move into A. The interval [$Bel(A), Pl(A)$] is the range of belief in A and measures the uncertainty degree in A.

D-S evidence theory provides a useful combination rule with which evidence from different sources can be combined. The combination rule is as follows:

$$m(\Phi) = 0 \qquad (7a)$$

$$m(A)=\frac{1}{1-k}\sum_{A_i\cap B_j\cap C_l\cap\cdots=A} m_1(A_i)\bullet m_2(B_j)\bullet m_3(C_l)\bullet\cdots \forall A\subset\Theta \quad (7b)$$

where,

$$k=\sum_{A_i\cap B_j\cap C_l\cap\cdots=\Phi} m_1(A_i)\bullet m_2(B_j)\bullet m_3(C_l)\bullet\cdots \quad (8)$$

Where

$$k=\sum_{A_1\cap A_2\cap\cdots\cap A_n=\Phi} m_1(A_1)\bullet m_2(A_2)\bullet\cdots\bullet m_n(A_n)$$

asures the degree of conflict between evidence sources. The coefficient $1/(1-k)$ is called a normalization factor and is used to avoid non zero mass from being assigned to the empty set Φ after combination.

3. 2 the algorithm process

By merging the spatial information into the classification decision, the paper proposed a remote sensing image classification method based on D-S evidence theory and neural networks .

First, the original image is smoothed with the smoothed image obtained.

There exists spatial correlation between neighbor pixels in remote sensing images and the correlation is represented by successiveness of distribution of ground cover to some extent, that is to say, a pixel (except edge pixels) neighbors should belong to the same class as the pixel does. A single pixel value in the smoothed image corresponds to the resulted value of smoothing the pixels in a rectangle range which is centered on the pixel at the same position in the original image and reflects the average value of neighbor pixels at the same position in the original image, so it contains the spatial information of the pixel at the same position in the original image. In classifying remote sensing images, the smoothed image can provide useful reference information for classification.

Next, the original image and the smoothed image are trained and classified by a BP neural network respectively.

After training and classifying the original image and the smoothed image respectively, we get two classification results (decisions) for the same pixel. The two classification results correspond to different ground cover which can be mutual supporting or can be mutual conflicting, i.e. resulting in uncertainty.

Next, in the paper, we regard the above two classification results as two pieces of evidence and fuse them by evidential reasoning[11~12]. For a certain pixel, the classification result of the original image reflects the pixel's single information and the classification result of the smoothed image reflects the pixel's neighbor pixels' information. Because of the correlation between pixels in remote sensing images, the classification result obtained by fusing the above two classification results exploits the correlation and improves the classification accuracy, reliability and robustness.

Let $T_1,T_2,\cdots T_k$ be different ground cover classes which is K in total and $\Theta=\{T_1,T_2,\cdots T_k\}$ be the frame of discernment. For a pixel, the actual outputs using the original image as the inputs of the BP network are normalized as $y_1^{(1)},y_2^{(1)},\cdots,y_k^{(1)}$ and the actual output using the smoothed image as the inputs of the BP network are normalized as $y_1^{(2)},y_2^{(2)},\cdots,y_k^{(2)}$. For the same pixel, the basic probability assignment function to two pieces of evidence m_1, m_2 are as follows:

m_1:

$$m_1(T_1)=y_1^{(1)},m_1(T_2)=y_2^{(1)},\cdots,m_1(T_k)=y_k^{(1)} \quad (11)$$

m_2:

$$m_2(T_1)=y_1^{(2)},m_2(T_2)=y_2^{(2)},\cdots,m_2(T_k)=y_k^{(2)} \quad (12)$$

Evidence m_1 and evidence m_2 are combined using the combination rule of D-S evidence theory (9) to produce a new evidence m. By adopting the rule that the basic probability assignment function of the target class to be determined should be maximum, we judge and classify according to evidence m with the fused result (decision) obtained.

Finally, the fused result (decision) is the final classification result of the original image.

4. Experimental results and performance comparison

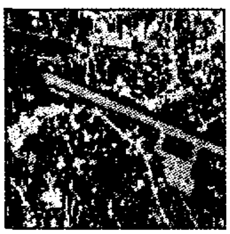
The tested image in the paper is a SPOT image of Ning Bo area. By human visualization, the image is divided as four categories: water, vegetation, soil, and constructor. We choose 20 samples for each category and there are 80 samples in total. The gray value range of [0,255] in every sample is normalized to the interval [0,1].

Each band of the remote sensing image is smoothed respectively with the smoothed images obtained. Then the smoothed images and the original image are used as the inputs of the BP neural network where the number of input nodes is 3 with one node representing one of three bands of the remote sensing image and the number of output nodes is 4 with one node representing one of four categories. We adopt the simplest coding scheme for the desired output: the output for correct classification is 1 and the output for error classification is o. The number of hidden nodes is 10.The BP neural network is trained by the method mentioned above .

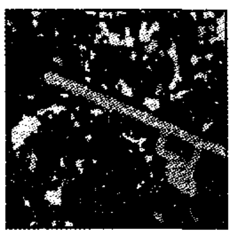
For comparison, the classification result of the area in Fig 3(a) (the rectangle area in it is an airport) using our method is compared with those obtained by the early BP neural network method and by using the sub images as the inputs of the networks separately. The classification results are showed as Fig 3(f), Fig 3(c), Fig 3(e) respectively.

(a) the tested image

(b)the smoothed image

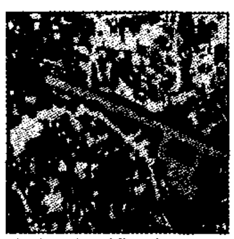


(c)the classification result of the original image



(d)the classification result of the smoothed image

(e)the classification result of using the sub images as inputs



(f) the classification result of our new algorithm

Fig.3 the tested images and the classification results

Airport belongs to the class of constructor by human visualization and its surroundings is mainly soil, so the desired classification result should distinguish airport from soil obviously meaning a clear airport contour .

Using early neural network methods to classify, it is difficult to attain the desired classification result. It can be seen form fig 3(c) that the contour of airport is not clear and there are lots of error classifications in its edge especially at the top of airport course. The reason for above phenomenon is that the spectrum feature vector of neighbor pixels at the edge of airport is similar to that of pixels belonging to the class of constructor i.e. the phenomenon of "same spectrum with different land matters" leads to the error classification. The classification method using sub images as the inputs of the network exploits the spatial information and it can be seen from Fig 3(e) that the classification effect of the whole image is improved but the contour of airport is not clear yet.

In our method, a certain pixel in the smoothed image (shown as Fig 3(b)) contains the spatial information of the pixel at the same position of the original image .The classification result of the smoothed image is shown as fig 3(d) and it can be seen from the whole image that lost of details information is lost . It is because the smoothing process is equivalent to a low-pass filter. But the airport contour in Fig 3(d) is very clear. We fuse the classification result of the original image with that of the smoothed image with evidence theory to obtain a new classification result as showed in Fig 3(f). It can be observed that the airport contour in Fig 3(f) is clearer than in Fig 3(c) and Fig 3(e) and the error classification phenomena is reduced thereby improving the classification effect of the whole image and the classification precision. The classification result after fusing the result of the original image and that of the smoothed image using D-S evidence theory is shown as fig

5. Conclusions

In traditional neural network methods for classifying remote sensing images, the phenomenon of "same spectrum from different land matters" is difficult to be conquered and the error classifications often appear on the borders of different classes thereby degrading the classification precision .In the classification of remote sensing image combing neural networks and evidence theory, we exploits the spatial information of the original image. In our method, the original image and the smoothed image are as the inputs of the neural network and the outputs of the neural network are fused with evidence theory with the final classification result obtained. So the proposed method exploiting both the pixel's self information and the pixel's spatial information decrease the classification uncertainty and improve the classification precision.

6. References

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