Landslide Fusion Detection Based on Features on Spatial Shape and Spectrum in Massive Data of Aerospace Remote Sensing

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Abstract: Aiming at the problems concerning poor and ineffective detection on landslide in massive data by aerospace remote sensing, landslide fusion detection method by spatial and spectral features based on neural network is proposed in this paper. A fusion detection model based on neural network and the typical fundamental spatial shape model of for landslide are established. The detection accuracy of landslide in remote sensing image is improved by SIFT algorithm feature matching and transformation, spatial shape feature similarity comparison. The rapid landslide detection and accurate extraction of disaster information is achieved by the fusion detection model, when disasters break out in large area. The proposed method is verified by application experiments in several aerospace remote sensing data. The experimental results show that our proposed method is superior to many other contrast algorithms, which improves the accuracy of landslide detection.

Index Terms: Big data of aerospace remote sensing; Spatial and spectral features modeling; Neural network; Remote sensing for disasters

1. INTRODUCTION

Landslide is one of the most common and pernicious geological disasters. It has the characteristics of wide distribution, great influence and strong destructiveness, poses a great threat to the lives and property of the people[1][2]. The southwest of China is a mountainous region with high susceptibility of landslide. In the case of earthquakes or heavy rains, many landslide disasters occur in a large area. Quickly detection and recognition landslide when disasters occur in wide range of mountainous region, and extraction of typical disaster information such as landslide location and acreage have important practical significance and research value in emergency rescue, disaster prevention and mitigation. With the rapid development of aerospace technology and imaging technology, it provides a new technical means for the detection of landslide by high-resolution, multi-band, multi-platform, multi-temporal remote sensing imaging technology.Zhang Haitao *et al.*[3] proposed a method for landslide detection by change feature. The independent component analysis (ICA) and minimum noise ratio transformation (MNF) is used to extract the difference information of the GF-1 images of the two phases, and the adaptive change threshold segmentation is conduct based on histogram. Accurate detection and recognition of landslide area is finally realized by these methods. Peng Ling *et al.*[4] takes Wenchuan earthquake area as an experimental object, spatial distribution of seismic landslides and their source, slip and accumulation areas are accurately detected by fusion of landslide spectral, texture, geometric and other image features and topographic features, and establishment of landslide recognition rules and models in remote sensing images of ZY-3 and GF-1. Li Zheng *et al.*[5]. proposed a landslide hazard detection method based on word bag feature for UAV image. The bag feature and support vector machine is used into landslide interpretation model, and rapid location and detection of montanic landslide on large scale and high-resolution images are realized.Ding A *et al.*[6] proposed a landslide hazard detection method based on convolution neural network (CNN) and texture change. The method extracts suspected landslide area by convolution neural network, then the suspected regions are identified accurately according to the texture change features extracted from remote sensing images before and after disasters. The experiment shows that the method can accurately detects landslide and extracting the disaster information for Shenzhen in 2015 by GF-1 remote sensing images. Ma H R *et al.*[7] proposes an automatic detection and recognition method for shallow landslides based on WorldView-2 multi-band optical remote sensing images. The features of soil brightness, vegetation index and shadows on the back wall of landslide are applied to target detection. The main image information is extracted by

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PCA, and the landslide points are detected based on automatic threshold segmentation. Lin Qigen *et al.*[8] proposes an object-oriented automatic landslide recognition method which integrates spectral, spatial, topographic and morphological features. The experiments show that the method can quickly and effectively detect large-scale landslides using 2.5m high resolution multi spectral images acquired by SPOT-5 after Wenchuan earthquake, which provides important information support for disaster analysis and emergency rescue. Li Z B *et al.*[9] proposes A semi-active landslide hazard area mapping method based on aerial remote sensing image. This method obtains difference image by analysis of change vector, and the candidate landslide hazard regions are extracted by threshold segmentation. Errors is eliminated by morphological method. Finally, the landslide region is detected and recognized quickly and accurately by edge grading evolution and regional grading evolution. Chen W T *et al.*[10] proposes a automatic landslide detection by data fusion technique using wavelet transform and taguchi methods.The DEM data extracted by airborne LiDAR and image acquired by QuickBird satellite are fused by wavelet transform. Object-oriented object classification based on target spectrum, texture and local spatial location features is carried out. Taguchi method is adopted to parameter optimization. Finally, accurate detection of landslides in tropical urban areas has been achieved.

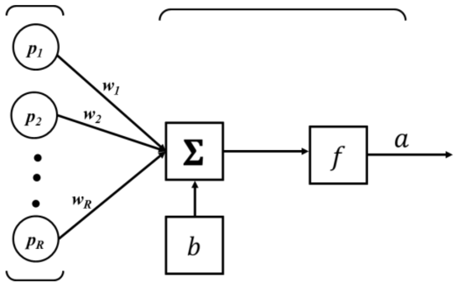
Massive remote sensing information acquired by aerospace multi-sensor has become the foundation of landslide detection and recognition. Traditional image interpretation, analysis and processing, information extraction technology are not compatible with the development status of massive remote sensing data, which has become an important bottleneck restricting the application of remote sensing technology in the field of geological hazard detection and identification. Therefore, In this paper, a method of landslide spatial-spectral feature fusion detection based on neural network is proposed based on the massive space-space remote sensing data, which is acquired by space multi-source optical remote sensing platform under the background of natural disaster emergency response. Accurate detection of landslide in typical space remote sensing images is realized by selection the typical landslide samples, construction of neural network detection model, spatial shape feature matching and similarity detection.

2. Landslide Detection Model Based on Neural Network by Spectral Features

The error back propagation network (BP neural network) is one of the most widely used and mature neural network models among many neural network models. BP neural network can approximate arbitrary non-linear mapping relations, and has good generalization ability[11][12]. This paper proposes a landslides detection method based on BP neural network according to their spectral features.

2.1 Neuron Model of BP Network

BP neuron basic model structure is constructed based on spectral features of remote sensing data. The nerve has R-dimensional input, and R is the same as spectral dimension of remote sensing image. Each input is given a corresponding weight w. The output of the neuron's transfer function is composed of weighted sum of R-dimensional inputs and deviation. The basic structure of BP network neurons is shown in Figure 1.

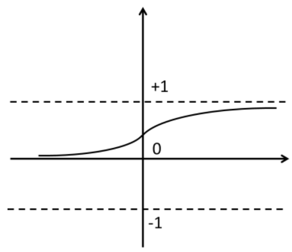


$$a = f(\sum p_i w_i + b)$$

Fig. 1 Basic structure of BP network neuron model

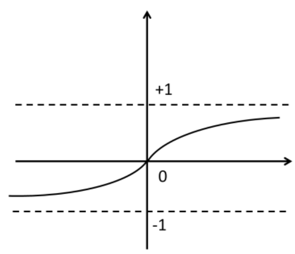
2.2 Transfer function model

In BP networks, Transfer function is very important. Typical transmission functions such as logsig, Tansig and purelin are chosen for BP neural networks.



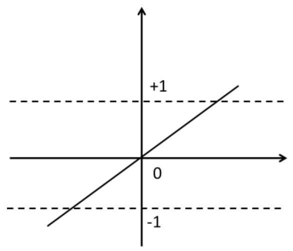
$$a = \log sig(n)$$

(a)



$$a = \tan sig(n)$$

(b)



$a = purelin(n)$

(c)

Fig. 2 Typical transfer functions of BP neurons

2.3 Structure of BP Neural Network

A detection model based on BP neural network is constructed according to the requirements of landslide identification and summary of experimental results. The model consists of an input layer, an output layer and two hidden layers, as shown in Figure 3. The dimension of input layer is the same as the spectral dimension of remote sensing image. The number of neurons in the first layer is 10, and the transfer function is logsig. The number of neurons in the second layer is 5, and the transfer function is tansig. The number of neurons in the output layer is 1, and the transfer function is purelin.

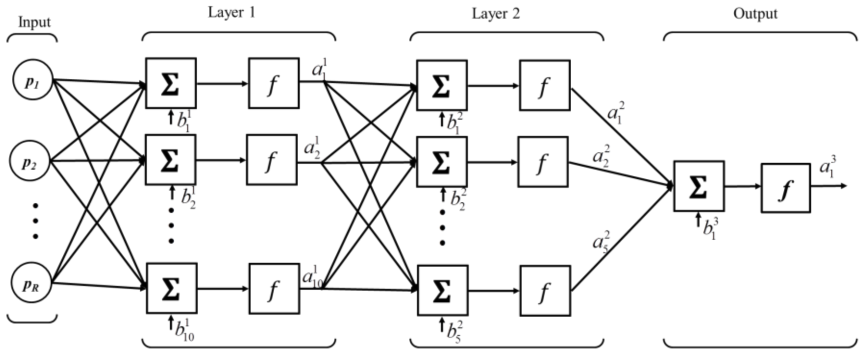


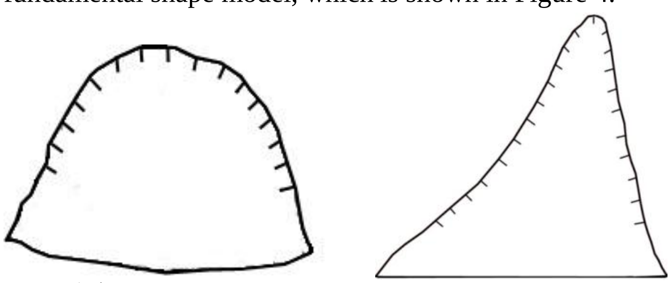
Fig. 3 Landslide detection model based on BP Neural Network

3. Landslide detection by Fusing Spatial Shape Features

In order to realize the application of landslide spatial shape features in target detection, SIFT feature matching and similarity detection algorithm are adopted based on landslide detection results by BP neural network, and accurate landslide classification and further recognition are carried out by fusing spatial shape features.

3.1 Construction of Landslide Typical Spatial Shape Model

The surface vegetation of landslide area will be subject to severely damage, and the newly exposed soil and rock is significantly different from the surrounding vegetation coverage in terms of brightness, hue and spatial shape. In this paper, we select two common basic shapes (dustpan shape and triangle shape) of landslide to construct fundamental shape model, which is shown in Figure 4.



（a）dustpan shape (b) triangle shape

Fig. 4 Fundamental shape models of landslides

3.2 Feature Detection and Matching Based on SIFT Algorithm

The detection results of BP neural network are matched with the landslide fundamental feature model by SIFT algorithm. The feature points extracted by SIFT algorithm have scaling invariance, rotation invariance and affine invariance, and they are also has certain anti-illumination and anti-viewpoint conversion performance[13][14]. So that, based on SIFT algorithm, feature point matching can be divided into five steps: scale space extreme value extraction, feature point location, feature direction assignment, feature description extraction and feature matching

For two-dimensional image I (x, y), the Gaussian scale space is defined as $L(x, y, t)$, which can be convoluted by Gaussian kernel G (x, y, t) and I (x, y):

$$L(x,y,t)=\begin{cases} G(x,y,t)*I(x,y) & t>0 \\ I(x,y) & t=0 \end{cases} \tag{1}$$

where,

$$G(x,y,t)=\frac{1}{2\pi t}e^{-(x^2+y^2)/2t} \tag{2}$$

Where x, y, are the pixel position coordinates of $L(x, y, t)$. t is the scale space factor. It is the variance of the Gaussian normal distribution, which represents the smoothing degree of the image.

To efficiently detect stable feature points in scale space, extreme value for Difference of Gaussian (DOG) in the scale space is used as judgment basis. The DOG operator is defined as follows:

$$\begin{aligned} D(x,y,t) &= (G(x,y,kt)-G(x,y,kt))*I(x,y) \\ &= L(x,y,kt)-L(x,y,t) \end{aligned} \tag{3}$$

The construction of $D(x,y,t)$ is shown in Figure 5. The DOG local extreme value is detected when the pyramid construction is completed. The extreme value point are funded and saved as the key point, by comparing each pixel with 8 pixels in the surrounding neighborhood of the same scale and 26 pixels in the 9×2 pixels corresponding positions

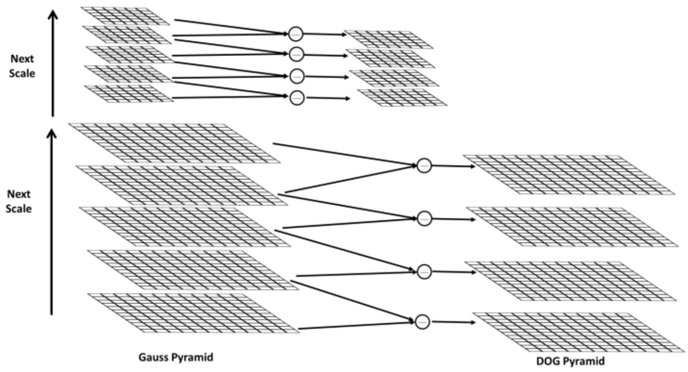


Fig. 5 Construction of Gauss image pyramid and DOG pyramid

The gradient mode and direction of each point in Gauss image are calculated by the gradient distribution of neighborhood pixels, then the direction of key points are determined.

$$m(x,y)=\sqrt{[L(x+1,y)-L(x-1,y)]^2+[L(x,y+1)-L(x,y-1)]^2} \tag{4}$$

$$\theta(x,y)=\tan^{-1}\frac{L(x,y+1)-L(x,y-1)}{L(x+1,y)-L(x-1,y)} \tag{5}$$

The gradient model and direction of the key points corresponding to the landslide detection results of BP neural network and the landslide typical shape model respectively are extracted by SIFT algorithm. the key points of optimal matching are found by Two-Dimensional norms, and the minimum Two-Dimensional norm point is selected as the optimal key matching point for feature matching between landslide typical shape model and neural network detection result.

3.3 Scale Space Transform and Similarity Detection

The optimal key feature matching points of typical shape model and landslide detection results by BP neural network are used to calculated scale transformation rate and rotation angle. The landslide fundamental shape model is transformed into a target template corresponding to the BP neural network landslide detection result by scale and rotation transformation[15]. The correlation detection method (see Formula 6) is used to detect landslide based on the results of BP neural network detection, which realizes the secondary utilization and further detection landslide by spatial shape features.

$$\rho(x,y)=\frac{\sum_{x=1}^{m}\sum_{y=1}^{n}\left[T(x,y)-\bar{T}\right]\times\left[I(x,y)-\bar{I}\right]}{\sum_{x=1}^{m}\sum_{y=1}^{n}\left[T(x,y)-\bar{T}\right]^2\times\sum_{x=1}^{m}\sum_{y=1}^{n}\left[I(x,y)-\bar{I}\right]^2} \tag{6}$$

4. Basic Flow of Landslide Detection by Spatial and Spectral Features Fusion Based on Neural Network

In order to make full use of spectral and spatial shape feature of remote sensing image, the landslide detection model are established based on BP Neural Network and landslide typical shape feature model. BP Neural Network is trained by landslide typical spectral samples and background spectral samples. The trained Neural Networks are used to detect the spectral samples of landslide. Then Ostu method is used to segment the results of Neural Networks. Feature detection and matching using fundamental shape models are done. A specific target template corresponding to the landslide detection result is formed through scale and rotation transformation from the fundamental shape model. With this template, landslide targets are further sorted and accurately identified and located. The basic flow of the proposed method is shown in Figure 6.

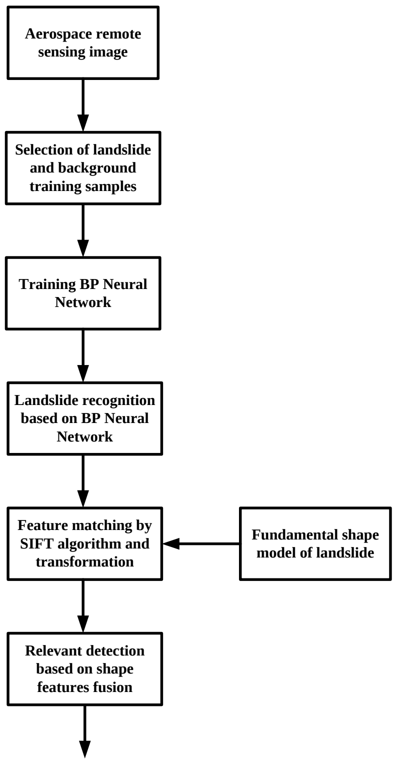


Fig. 6 Basic flow chart of the proposed method in our paper

5. Experiments and analysis

5.1 Experiment 1

A landslide of about 68m×55m in the west of a college is selected as the research object. The experiment of landslide detection in high resolution satellite remote sensing data of WorldView-4 was carried out. The overall situation of the landslide area is shown in Figure 7. In order to verify the proposed method of landslide detection, The proposed algorithms is realized by programming in MATLAB. The Bayesian classifier and SVM algorithm are compared with the proposed algorithm[16][17]. The selected training sample distribution and the detected sample distribution are shown in Figures 8 and 9. The fundamental shape model(dustpan shaped) of the landslide is shown in Figure 4(a).

Fig. 7 WorldView-4 remote sensing image of landslide area

Fig. 8 Distribution of training samples (Red for landslide samples, green for background vegetation samples and blue for road samples)

Fig. 9 Detecting sample distribution
(Red is landslide test sample, blue is background test sample)

The selected BP neural network model is described in Section 2.3, which maximum number of training is 500, accuracy of training requirement is 0.01, learning rate 0.01. Gradient descent method is used for training the net. The training process and results of the our BP neural network are shown in Figure 10 and 11.The kernel function of SVM algorithms is linear. Sequential Minimum Optimization (SMO)is used for searching for classification hyperplanes. The results of Bayes classifier, SVM algorithm and the proposed neural network algorithm for landslide detection are shown in Figure 12. The accuracy and error of landslide detection are shown in Table 1.

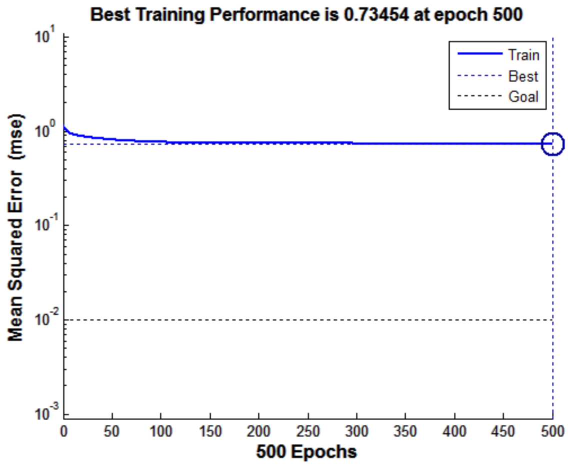


Fig.10 The training performance of our neural network

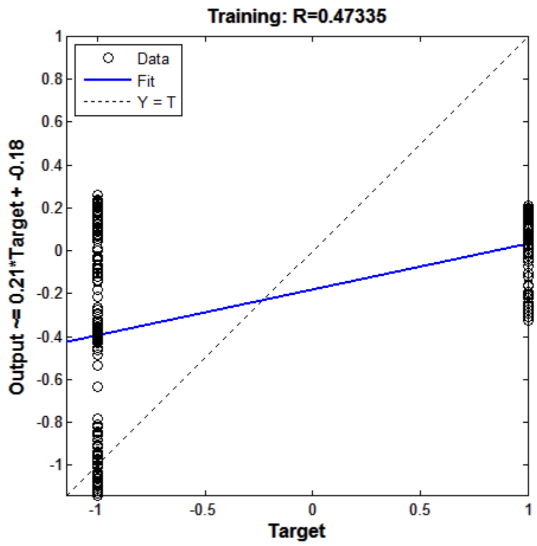
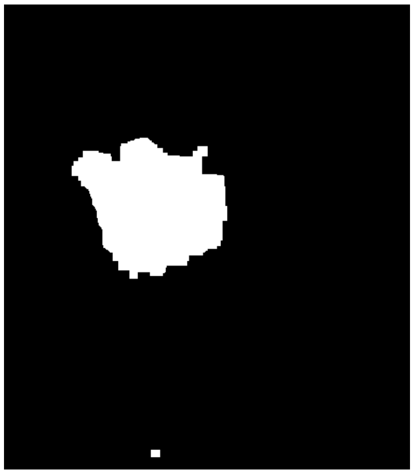
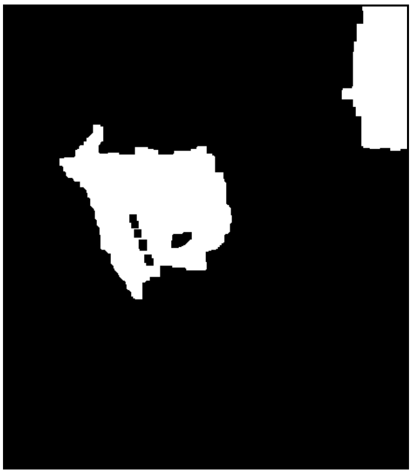


Fig.11 The regression of our neural network

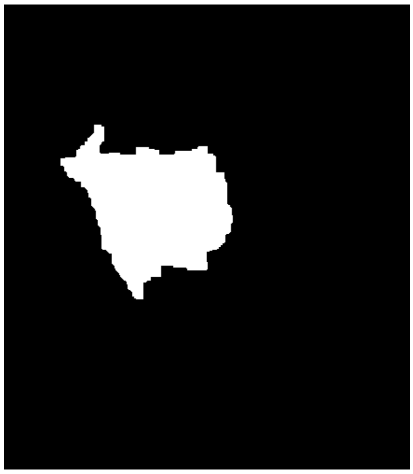
(a) Landslide detection results by Bayes classifier



(b) Landslide detection results by SVM



(c) Neural Network landslide detection method based on spectral features



(d) Landslide detection result based on fusion of spatial shape and spectral features (The Final method proposed in this paper)

Fig. 12 Landslide detection results in WorldView-4 remote sensing images

Table 2 Accuracy and error of four algorithms

	Bayes Classifier	SVM	NN	NN+shape feature (The final method of this paper)
Correct detection rate	93.26%	80.78%	80.91%	85.50%
Missing alarm rate	6.74%	19.22%	19.09%	14.50%
False alarm rate	6.81%	1.05%	2.28%	1.27%

As can be seen from Fig. 12 and Table 1, Bayes classifier has higher accuracy in landslide detection, but higher false alarm rate than other methods, and many non-landslide pixel points are incorrectly identified as landslides. The detection rate of SVM is about 80%. Due to the lack of spatial shape information, the correct detection rate is not high. The results of landslide detection based on spectral feature and neural network are similar to those of SVM, Both of them are unsatisfied. The landslide detection method based on spectral feature and neural network can not accurately identify the blue rectangular roof in the upper right corner of the image, which is made a mistaken for a landslide. Landslide detection method based on Neural Network and spatial-spectral feature fusion can accurately distinguish landslides from roofs, and accurate detection of landslide area is realized by spatial feature fusion. The allover detection accuracy of our proposed method is better than other methods.

5.1 Experiment 2

A landslide near a mountain road from Nanchuan District to Wansheng District of Chongqing City was selected as the research object. The experiment of landslide detection in high resolution satellite remote sensing data of WorldView-2 was carried out. The overall situation of the landslide area is shown in Figure 13. The selected training sample distribution and the detected sample distribution are shown in Figures 14 and 15. The basic shape model(Triangle) of the landslide is shown in Figure 4(b).

Fig. 13 WorldView-2 remote sensing image of landslide area

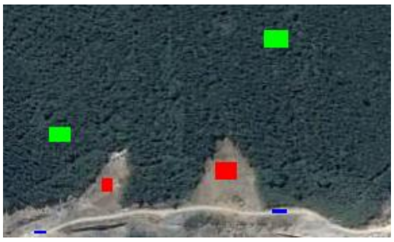


Fig. 14. Distribution of training samples (Red for landslide samples, green for background vegetation samples and blue for road samples)

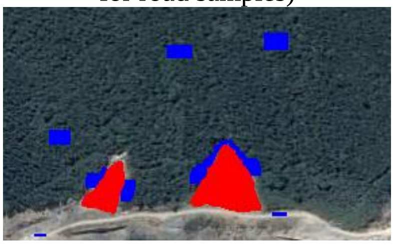


Fig. 15 Detection sample distribution
(Red is landslide test sample, blue is background test sample)

The parameters of the selected BP neural network model, Bayes classifier and SVM algorithm are the same as Section 5.1 Experiment 1. The training process and results of the our BP neural network are shown in Figure 16 and 17.The results of landslide detection by three algorithms are shown in Fig. 18. The accuracy and error of landslide detection are shown in Table 2.

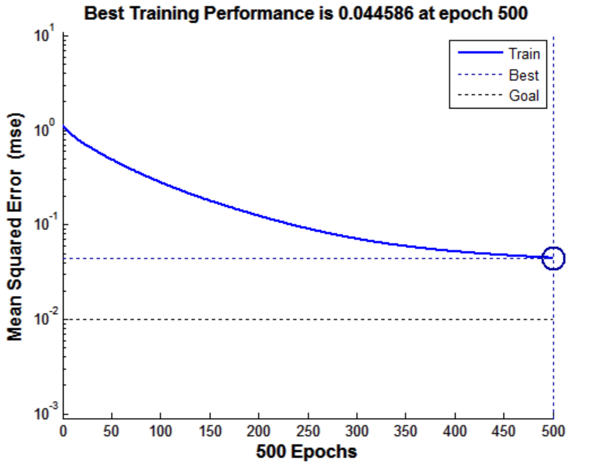


Fig.16 The training performance of our neural network

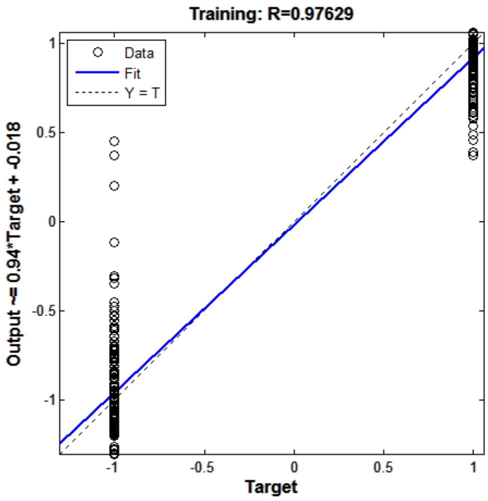
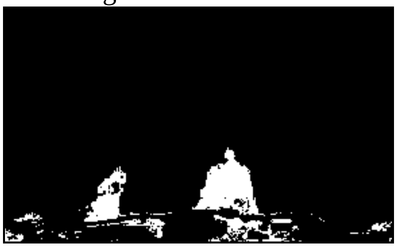
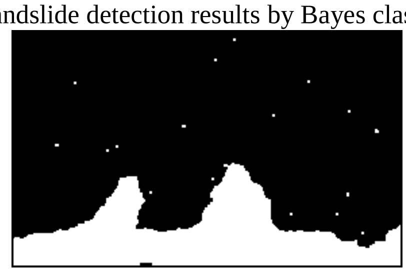


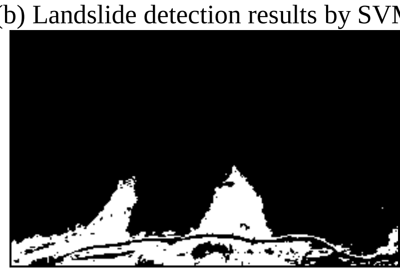
Fig.17 The regression of our neural network



(a)Landslide detection results by Bayes classifier



(b) Landslide detection results by SVM



(c) Landslide detection result based on fusion of spatial shape and spectral features (The Final method proposed in this paper)

Fig. 18 Landslide detection results in WorldView-2 remote sensing images

Table 2 Accuracy and error of three algorithms

	Bayes classifier	SVM	NN+shape feature（(The final method of this paper)
Correct detection rate	73.71%	100%	95.52%
Missing alarm rate	26.29%	0%	4.48%
False alarm rate	0.36%	8.78%	1.38%

As can be seen from Fig. 11 and Table2, Bayes classifier has poor accuracy in landslide detection, and 26% of landslide test samples are not detected in landslide remote sensing image of this area. The correct detection rate and missing alarm rate of SVM are very good, but the false alarm rate is high. The proposed algorithm achieves higher overall recognition rate, by making use of spectral and spatial shape features, and it can maintain a low false alarm rate. detection result of our proposed method is better than the other two algorithms.

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6. CONCLUSION

A landslide fusion detection method by spatial and spectral features based on neural network is proposed in this paper, from the angle of fusion and utilization of spectral features and shape features of aerospace remote sensing images. The paper focuses on researches such as construction of BP Neural Network landslide detection model based on spectral features, feature matching and transformation by SIFT algorithm, Similarity Detection based on fundamental shape model. Landslide detection based on space optical remote sensing image is realized, which is a new way and method of landslide area detection by timely and efficient use of aerospace remote sensing data and disaster information extraction for disaster relief agency.

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