Nature Environment and Pollution Technology
An International Quarterly Scientific Journal
p-ISSN: 0972-6268
e-ISSN: 2395-3454
Vol. 18 No. 1 pp. 335-341 2019

Original Research Paper Open Access

Accuracy Assessment of Land Use Classification Using Support Vector Machine and Neural Network for Coal Mining Area of Hegang City, China

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Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 18-07-2018
Accepted: 21-09-2018

Key Words:
Coal mining area
Land use classification
Support vector machine
Neural network
Texture feature

ABSTRACT

Information of land use plays a key role in the ecological systems. Most studies focus on the land use studies in large cities or large areas, but rarely carry out a land system in vulnerable areas. In this study, the size of 1000×1000 pixels in Hegang coal mining area was used as the experimental area. Based on Landsat TM image of September 8, 2010, principal component analysis (PCA) and optimum index factor (OIF) were used to select the best band combination of images, and the texture statistics, texture features and spectral information of the homogeneity, contrast, entropy and angular second moments of the remote sensing image were extracted by using the gray level co-occurrence matrix texture feature. A sample of 600 pixels was selected, of which 400 pixels were used as training samples and 200 pixels as test samples. The results show that the support vector machine (SVM) and neural network (NN) classification technique are used to classify land use in coal mining area. The overall accuracy obtained was 92.40% and the kappa statistics 0.9126 for SVM, 90.90% and 0.8930 for NN, respectively. This study provided a comprehensive extraction of samples to improve the accuracy method. The SVM and NN classification results show that SVM classification method is superior to NN classification method, and it can effectively be utilized for Landsat TM images to identify land use types in coal mining areas.

INTRODUCTION

Information on land use/land cover (LULC) plays a key role in natural resource management (Wentz et al. 2006, Soffianian et al. 2015). LULC mapping using satellite images has become widely popular in the last decades (Sen et al. 2015). Coal city as a special urban group, land use and land cover of areas in the vicinity of mining sites are significantly affected by the corresponding mining activities and consequently change faster than other areas (Rathore et al. 1993). Remote sensing and GIS tools have been used extensively in the mining industry for various purposes such as mineral exploration, modelling and monitoring, mine planning, and environmental impact assessment (Vander Meer et al. 2012, Karan et al. 2016). Numerous researches have been published on comparison of different remote sensing image classification algorithms used for LULC mapping (Vorovencii 2014a). Although these classification methods are very effective in land-use extraction, because of the multi-scale and complexity of the objects, the phenomenon of "homologous spectrum" and "foreign matter homology" exists, which cannot simply use spectral features or a classification method for remote sensing image classification. Support vector machine (SVM) is a recent non-parametric supervised statistical machine learning technique that aims to find an optimal hyperplane (Cortes et al. 1995), which separates the multispectral feature data into discrete predefined clusters consistent with training datasets. The classification errors in the individual images affect the final accuracy of change detection. In case of these techniques, it is very important to develop high accuracy classifications for each satellite image (Lu et al. 2004). Traditional support vector machine (SVM) has adverse effects on classification accuracy. Therefore, we use SVM classification method which is combined with texture information and spectral information to extract the information of land use in Hegang coal mining area, so as to improve land use classification accuracy and better use of remote sensing technology in the application of LULC.

MATERIALS AND METHODS

Study site: Hegang is located in the hilly region of the eastern foot of the Little Xing'an Mountains and the plains at the junction of the Songhua River and Heilongjiang River, in Northern China (47°03'30"- 48°21'00" N and 129°39'50"- 132°31'00"), as shown in Fig. 1. The coal mining area is located in the northwestern region of Hegang, selected as a typical research area. The climate of Hegang City is affected by the temperate continental monsoon, it is cold and dry in winter and warm and rainy in summer. The average annual temperature is 1.0-4.6°C, the average annual frost-free period is about 125 days, and the average annual rainfall of about 608.5 mm. The study area as a whole showed a low trend in the south and high in the north, with the hills in the north and the plains in the south.

Remote sensing image data preprocessing: Landsat5 TM surface reflectance data of 8 September 2010 was collected from USGS Earth Explorer. The image was standardized and projected to the projection system, Universal Transverse Mercator (UTM) Zone52N Datum WGS 1984 projection using ArcGIS10.5. Image collected is based on the local climate characteristics of choice, this time period is rich in species, has bright colours, and easy to identify. Remote sensing image preprocessing includes 2% linear stretch image enhancement processing, crop cutting, noise removal and other processing to reduce the classification error. According to the land use classification criteria and the actual situation of the site, the land use types of the test area are divided into 8 categories: residential land, coal mine land, forest land, grassland, water area, cultivated land, unused land and transportation land.

METHODS

Classification methods: The performance of two classification algorithms was examined. These algorithms include neural network (NN) and support vector machine (SVM). The landsat TM images are classified by the two classifiers using the same training dataset per case study.

Support vector machine (SVM) technique is based on statistical learning theory presented by Cortes and Vapnik in 1995s. The SVM classifier is a modern, powerful supervised classification method that can handle multiple-band imagery having high resolution and large segmented satellite data with ease when compared to other classification techniques, where attribute table management becomes difficult (Shivesh et al. 2016). It can solve some practical problems such as high dimension data, small sample, non-linearity and so on. It has high precision and stability for the classification of ground objects. Set the training sample is $\{x_i, y_i\}_{i=1}^{N}$, among them $x_i \in R^n$, indicates the input mode and $y_i \in \{-1,1\}$ indicates the target output. Set the optimal decision surface equation: $W^T x_i + b = 0$, the weight vector W and the offset b must satisfy the constraints:

$$y_i(W^T x_i + b) \geq 1 - \xi \quad ...(1)$$

Where ξ is the slack variable under the linearly indivisible condition, which indicates the degree of deviation of the model from the ideal linear case. The following optimization formula can be deduced based on the principle that the average error of the training sample classification data is the smallest.

$$L(w,\xi) = \frac{1}{2}W^T W + C\sum_{i=1}^{N}\xi \quad ...(2)$$

C>0 is the error term penalty parameter. The SVM locates a linear separating hyperplane with the maximum margin in this higher dimensional space. By using the Lagrange multiplier method, the optimal decision surface can be transformed into the following constrained optimization problems:

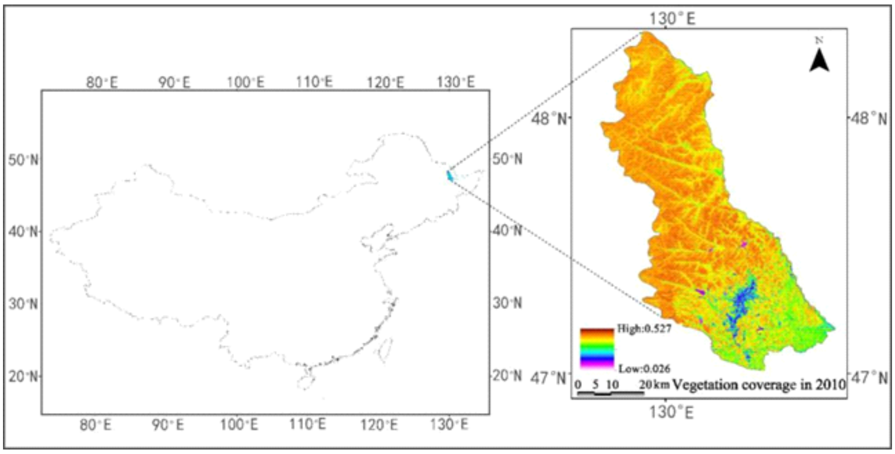


Fig. 1: Location of the study area.

$$Q(a)=\sum_{i=1}^{N}a_i-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}a_i a_j y_i y_j K(x_i,y_j) \quad ...(3)$$

Where, $\{a_i\}_{i=1}^{N}$ is the Lagrangian multiplier and $K(x, x_i)$ is a kernel function and satisfies the Mercer's theorem. The kernel function has many forms, including linear, radial basis function and polynomial. With different kernel function and parameter setting, its classification effect is different.

Neural network (NN) is a nonparametric algorithm that does not make any assumptions on the distribution of data (Vorovencii 2014). One challenge in using NN classifier is to decide the appropriate network architecture and training parameters. Saleh et al. (2015) have tested different combinations of network values in a neural network algorithm and determined the classification with the highest complete accuracy for each case study. The optimized network parameters include training threshold contribution, tested with three values of 0.5, 0.7 and 0.9; training rate, tested with three values of 0.1, 0.2 and 0.5; training momentum, tested with four values of 0.1, 0.2, 0.5 and 0.9; structure of hidden layers 1 and 2; and a fixed logistic activation function (Saleh et al. 2015).

Optimum band combination selection based on PCA and OIF: Principal component analysis (PCA) represents a method used in many applications for remote sensing, including land use/land cover change detection (Fung et al. 1987). Its main advantage is the capacity to reduce the size of the data with minimum information loss (Iosif 2014). All variables were submitted to PCA to reduce the data dimensionality by performing a covariance analysis between the factors. The transformed first principal component usually contains more than 80% of the total information, which can reflect the total radiation intensity of the object, and can effectively extract the linear features, thus improving the classification rate.

The combination of the best bands is an important prerequisite for the visual interpretation and feature extraction of remote sensing images. According to different uses, different bands are selected as the RGB component to synthesize the RGB colour images. The colour saturation of the synthesized images can display rich feature information or highlight a particular aspect of information, convenient and efficient identification of objects. Band selection is usually based on the combination of the maximum amount of information band and the minimum information between the relevance of the principle of selection, the use of correlation coefficient analysis of the degree of information overlap between bands. The higher the correlation coefficient, the higher the data similarity, otherwise the data redundancy is low. The PCA is used to remove the redundant information of each band. The first three components contain 92.63% of the information in all the bands, and the first three components can be combined to help the classification of RGB, through the statistical calculation of the inter-band correlation coefficient matrix (Table 1).

From Table 1, we can know that Band4 has highest independence, Band2 and Band3 correlation is significant, the correlation coefficient is greater than 0.9, Band2 and Band3 have consistent spectrum. But as only one can be selected, Band4 and other band correlation is small, it has strong independence and high-quality information, so the choice of band Band4 as a mandatory band. Band 5, 6 and band 5, 1 correlation is low, Band7 is slightly superior to Band5, 6. According to the above analysis, the best band combination is 742 and 743, and the best band combination is quantitatively evaluated by using the best band index (OIF) to obtain the best band combination.

The OIF index takes into account the standard deviation, which reflects the degree of dispersion of the data and the correlation coefficient that reflects the correlation between the bands. Band combination of the larger standard deviation and the smaller correlation coefficient, indicate a good band combination. The result shows that the order of OIF index is Band743> Band742. The results show that Band743 is the best band combination, and its information is the most abundant. In practice, it will be found that due to the complexity of surface features, the optimal band combination of different landforms will change accordingly, so the most good combination of bands is selected that will contribute to land-use classification.

Texture feature analysis based on gray level co-occurrence matrix: The gray level co-occurrence matrix is a commonly used method to describe the texture features, which can reflect the gray space between any two points in the image by the matrices formed by angular second moment joint probability density between the image gray values related properties (Wu et al. 2005). Texture is made up of alternating gray-scale spatial distribution, and each object has a certain spatial correlation. Therefore, we used the statistical index of gray-level co-occurrence matrix to describe the texture feature, after selecting the appropriate texture scale and indicators to optimize the classification results.

Remote sensing spectral data provide a large number of spectral features of landforms, and the use of spectral information for land use classification of remote sensing images can reduce the error of visual interpretation of classification. However, spectral information classification also has certain drawbacks. Spectral information of a single place of its classification effect is better, but the spectral confusion of the classification effect is more broken. The texture feature of each feature is different. It is effective to improve the

Table 1: Band correlation coefficient matrix.

Band	Band 1	Band 2	Band 3	Band 4	Band 5	Band 6	Band 7
Band 1	1	0.9185	0.9247	-0.1774	0.5381	0.6466	0.8140
Band 2	0.9185	1	0.9571	0.0155	0.6094	0.5448	0.7800
Band 3	0.9247	0.9571	1	-0.1509	0.5809	0.5902	0.8158
Band 4	-0.1774	0.0155	-0.1509	1	0.3378	-0.3298	-0.1144
Band 5	0.5381	0.6094	0.5809	0.3378	1	0.3898	0.8109
Band 6	0.6466	0.5448	0.5902	-0.3298	0.3898	1	0.6469
Band 7	0.8140	0.7800	0.8158	-0.1144	0.8109	0.6469	1

Table 2: Accuracy assessment using the confusion matrix based on the SVM and NN technique.

Cover	SVM		NN	
	PA(%)	UA(%)	PA(%)	UA(%)
Forest land	92.50	96.52	98.33	97.52
Grassland	86.87	66.67	80.00	72.73
Water area	97.50	100.00	100.00	100.00
Cultivated land	90.91	99.17	92.42	84.14
Residential area	100.00	100.00	94.79	98.91
Coal mine land	93.33	100.00	95.00	100.00
Unused land	89.29	82.42	86.11	67.39
Transportation land	86.90	85.88	58.55	100.00
OA(%)	92.40		90.90	
Kappa coefficient	0.9126		0.8930	

Note: UA-user's accuracy, PA-producer's accuracy, OA-overall accuracy.

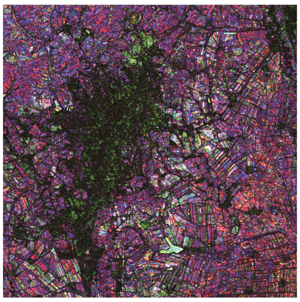
classification accuracy by combining the spectral information with the image texture feature extraction. The texture feature extraction is the most widely used and the best.

Gray matrix co-occurrence matrix: Each matrix element describes the probability that the gray level j occurs with the gray level i as the starting point when the pixel distance d is separated by a certain distance in the q direction, and the probability that the gray level is j is denoted as p (i, j, d,) (Harlick et al. 1973). The results show that 17×17 is the best processing window, and the gray level is 64. According to the selection of the field and the texture index, the homogeneous, contrast, angular second moment, and entropy of the four indices were extracted for texture analysis (Fig. 2). The angular second moment image can highlight the construction land and water information, contrast can clearly identify the residents, roads and other information; information entropy can describe the spatial complexity and chaos of the study area. You can use entropy threshold to extract unused land, while the homogeneity of the extraction of water is more accurate. The four eigen values of 0°, 45°, 90° and 135° in the four directions are more accurate and the mean value of the feature values in the four directions varies with distance.

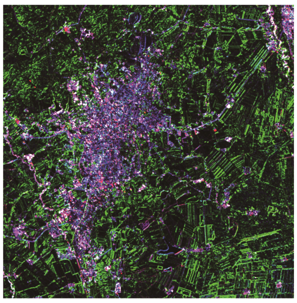
RESULTS AND DISCUSSION

Analysis of classification results: According to the field survey dataset, the land use types of the study area were divided into 8 types, which were cultivated land, forest land, grassland, water area, residential area, coal mine land, unused land and transportation land. Using the ROI separability to determine the degree of discrepancy between categories, the statistical distance between classes is based on Jeffries-Matusita distance and transformed divergence (TD) can be used to measure the separability of training samples (Mallet et al. 2011). In the sample selection, we should not only consider the spectral characteristics, the distribution of regional characteristics and radiation characteristics, but also consider the edge of the map, topographic factors such as coverage characteristics, combined with field surveys, to ensure the selected sample representative in order to obtain a higher precision. The reference datasets of each image were randomly divided into training and validation set. Training sets included 400 pixels of each land cover and used for image classification. Validation sets included 200 pixels of each land cover and were used for classification accuracy assessment.

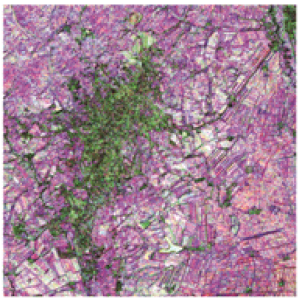
Eight different land uses (cultivated land, forest land,



(a) Angular second moment



(b) Contrast



(c) Entropy

(d) Homogeneity

Fig. 2: The result texture analysis of gray level co-occurrence matrix.

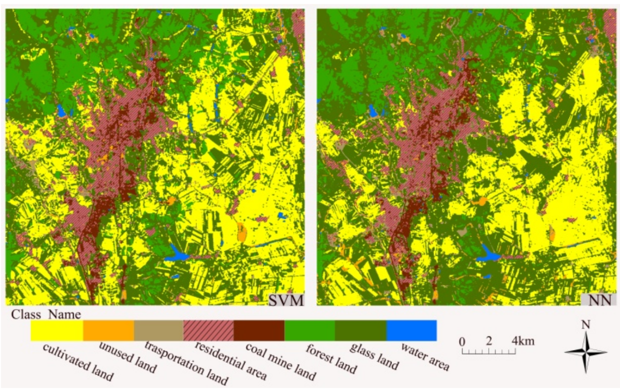
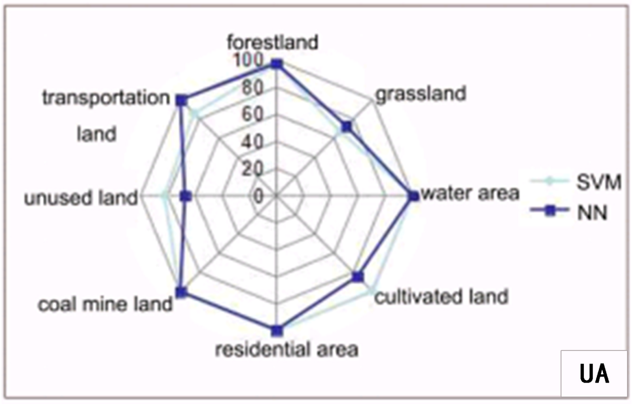


Fig. 3: The classified images of support vector machine and neural networks.

grassland, water area, residential area, coal mine land, unused land and transportation land) were successfully delineated using SVM and NN classification technique (Fig. 3). The classification results show that SVM classification and NN classification technique based on spectral information and texture features can be successful to extract the features, which can better highlight the details of the features, and the classification results are closer to the actual situation.

Accuracy assessment: After the land use classification process, it is important to assess the accuracy of the classified image, to peg and quantify mapping or classification errors



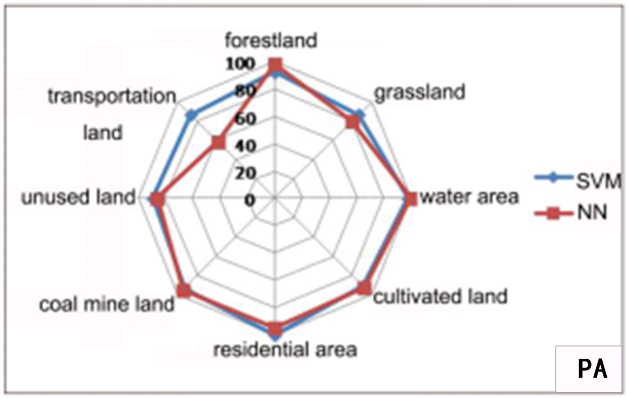


Fig. 4: Classification accuracy comparison image of SVM and NN methods.

(Koukoulas et al. 2001, Kalkhan et al. 1995). There are many precision evaluation methods available, the most commonly used technique is the confusion matrix method. In this method, a simple cross tabulation of the mapped class label against that observed in the ground or reference data is employed for a sample of cases at specified locations (Canters 1997). Classification accuracy and Kappa coefficient can reflect the accuracy of classification results of remote sensing images in the whole study area. Based on the texture and spectral information, the classification of land use in coal mining area was carried out, and the confusion matrix was used to classify and evaluate. The producer's accuracy is derived from the total number of the correct pixels of a class divided by the total number of the pixels. The user's accuracy is measured by total number of the correct pixels of a class divided by the total number of the pixels (Simitkumar et al. 2014). Table 2 presents the user's accuracy, producer's accuracy, and overall accuracy independent of class probability as our focus is classifier performance that is not site-specific.

The results revealed that the classification accuracy of ROI based on texture feature and spectral information technology is high, the overall accuracy of two classification techniques is more than 90%. Using SVM classification technology, user's accuracy of water area, residential area and coal mine land reached 100%. The classification error of forest land, cultivated land is also very small, with the accuracy of 96.52% and 99.17%, respectively. But grassland classification accuracy is low, which is related to grass growth habit, easy to be confused with other features. The producer's accuracy of grassland classification is 20.2% higher than that user accuracy in SVM. Using neural network classification technique, the overall classification accuracy is low with 1.5% support vector machine. But the classification accuracy of forest land, transportation land which used NN classification technique is higher than that of SVM classification. Unclassified user classification accuracy is only 67.39, 15.03% less than SVM classification accuracy.

The accuracy of SVM and NN classification is compared with the accuracy of the users. From Table 2 and Fig. 4, the user's accuracy of land use type is higher than that of NN classification by using SVM classification method, except for transportation land and grassland. The producer's accuracy comparison image also shows the classification advantage of SVM technology. The producer's accuracy of transportation land is low in NN classification, except for other types of land use accuracy which are about the same as SVM classification accuracy.

CONCLUSION

In this research, the training samples and test samples were selected based on the texture feature, and spectral information and different classification algorithms were examined for coal mining area LULC classification. The SVM and neural network methods performed high classification accuracy with a slight out performance of SVM (92.40%) over NN (90.90%). From the algorithmic perspective, results indicate that for coal mining area land use, SVM was superior to NN in overall classification accuracy as well as individual classification accuracy for many classes. One of the advantages of the SVM algorithm for land cover mapping is producing highly accurate classified images from small training sets (Halder et al. 2011). This advantage helps environmental and natural resource managers to provide LULC maps with accurate information quickly, thus saving them time and cost (Mountrakis et al. 2011). The setting of the NN threshold parameter is important for classification accuracy, NN of training algorithm adjusts the weights and node thresholds of the nodes in a crossed way, which can reduce the error to a minimum, and generate a good classified image.

SVM and NN were superior to other classification methods in supervised classification, but SVM classification is more accurate than NN in land use classification of coal mining area. In our study, using the combination of PCA and OIF method to select the optimal band combination, the 743 band imaging bright colours conductive to visual interpretation of objects. Texture feature and spectral information analysis method to select the appropriate sample and land use classification were carried out using SVM and NN techniques. The above method is combined to make the classification accuracy higher, which effectively solves the problem of classification. This is the first step towards the provision of ecological services to environmentalists and policy makers, and is the key to sustaining sustainable development.

ACKNOWLEDGMENTS

The authors would like to express gratitude to the research grant support kindly provided by China Postdoctoral Science Foundation (Grant No.2017M621229), Postdoctoral Science Foundation of Heilongjiang Province (Grant No.LBH-Z17001), the National Natural Science Foundation of China for Young Scholars (Grant No.41101177, 41301081), Philosophy and social science program in Heilongjiang Province (Grant No.17GLD173, Grant No. 16GLC04), Scientific Research Foundation for the Returned Overseas Chinese Scholars, Heilongjiang Province, the University Strategic Reserve Personnel Abroad Research project funded by Heilongjiang Province, University Nursing Program for Young Scholars with Creative Talents in Heilongjiang Province (ecological environmental vulnerability and land reclamation in Coal Mining Areas of Heilongjiang Province).

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