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Stand species identification using GF-2 imagery and airborne LiDAR data based on SVM classifier

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Stand species identification using GF-2 imagery and airborne LiDAR data based on SVM classifier

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Abstract. Stand species recognition is one of the key topics in forest research. The new GaoFen-2 (GF-2) satellite imagery contains detailed spectral and texture features. LiDAR data can provide abundant forest structure information. Using deep learning algorithms to identify forest types from optical and LiDAR data can improve recognition accuracy effectively. In this paper, the GaoFeng forest farm of Guangxi Zhuang Autonomous Region is taken as the experimental area, the mean and variance of GF-2 red-green-blue triple band spectra are taken as the spectral characteristics, and the corner two matrix, entropy, contrast and correlation in the gray level co-occurrence matrix are taken as the texture characteristics, a canopy height model (CHM) derived from LiDAR data is built as the structural characteristics, comparing the classification accuracy of using spectral feature, texture feature and structure information or spectral feature, texture feature based on SVM deep learning algorithm to classify in different resolution and different classification levels. The results show that the accuracy of the specific tree species classification by SVM classifier using 2 m-resolution fused GF-2 image combined with spectral, texture and structure features is high, the total classification accuracy is 95.65%, and Kappa coefficient reaches 0.93. As a contrast, the results of 4m-resolution fused GF-2 image using spectral and texture feature classification are poor. Combining the spectral and texture information of forest and the structural information reflected by LiDAR point cloud data can achieve significantly better classification results than each single feature. Compared with several traditional supervised classifiers, the new method needs less specialization and is more beneficial to the large-scale promotion of forestry classification.

1. Introduction

Forest is one of the most important natural resources for human beings. It not only plays an important role in soil and water conservation, but also can effectively improve our living environment, regulate climate and prevent environmental pollution. In the survey of forest resources, stand species identification provides basis for forest investigation, afforestation, management, planning and design. With the rapid development of remote sensing technology, it is more conveniently and efficiently to obtain forest images and complete forest type identification by remote sensing, which has become the main way of forest type classification.

Compared with low-resolution remote sensing image, high-resolution remote sensing image has richer texture information and clearer image details[1], which is more suitable for forest type recognition. When using high spatial resolution remote sensing image to identify forest types, the shape, spectrum and texture features in the image are combined to make the recognition effect more accurate[2]. Gray level co-occurrence matrix is a commonly used method for texture information extraction, among which angle two matrix (ASM), entropy, correlation, contrast, mean, variance, homogeneity and dissimilarity are eight commonly used gray level co-occurrence matrix texture statistics. According to Hou Qun Qun et al's analysis[3], four kinds of gray level co-occurrence matrix texture statistics (ASM, entropy, correlation and contrast) have low redundancy and high robustness.

The combination of hyperspectral data providing detailed spectral information of forest species and airborne LiDAR data providing structural parameters of forest species is helpful to further improve the accuracy of forest classification[4]. Dalponte et al. (2012) [5] conducted tree species classification experiments in complex forests by using hyperspectral data and airborne LiDAR data, which confirmed that the structural information provided by LiDAR data is conducive to improving the accuracy of forest tree species classification; Alonzo et al. (2014) [6] conducted tree species identification on the canopy scale by combining LiDAR data and hyperspectral data, and the results showed that the accuracy of tree species classification improved 4.2% after adding LiDAR data.

Compared with the traditional algorithm, the deep learning algorithm is more simple and efficient. It has become an increasingly important point to combine LiDAR and hyperspectral data and other multi-source remote sensing data using the deep learning algorithm for forest type recognition. For example, FERET et al. (2012) [7] identified nine specific tree species of tropical forest in Hawaii Island, which was based on tree height and intensity variables to participate in clustering and using semi supervised support vector machine (SVM) classification method; Naidoo et al. (2012) [8] obtained the optimal classification result (accuracy 87.68%) in the identification of tropical tree species in Africa, combining tree height features extracted from LiDAR discrete point cloud data with NDVI extracted from airborne hyperspectral data using random forest model. Based on the structural difference of airborne LiDAR and the spectral difference of EO-1 hyperion , Ceballos et al. (2015) [9] estimated the forest species diversity in the Andean mountains ($R2 = 0.651$; RSE = 3.69); Liu et al. (2017) [10] used the RF classification model to classify 15 common urban tree species with an overall accuracy of 70%, combing the structural parameters extracted from LiDAR data and the vegetation index extracted from hyperspectral data.

2. Materials and methodology

2.1 Research area

The experimental area of this study is part of the state-owned GaoFeng forest farm in Guangxi Zhuang Autonomous Region, which is located at 22 °44 '- 23 ° 32' N to 108 °3 '- 108 °51' E. The forest farm in Xingning District, which is located in the south of the tropic of cancer and belongs to humid subtropical monsoon climate, with abundant sunshine, mild climate, abundant rainfall, little frost and snow, long summer and short winter and annual average. The temperature is about 21.6 ° which is suitable for the growth of forest vegetation. The terrain inclines are from northeast to southwest, showing gentle block. Except for the low mountains above 400m in the north and east, such as Liuhuan mountain, Gaofeng mountain and a small number of secondary platforms about 110m above sea level, the rest areas are flat and wide, which are suitable for the growth and cultivation of forest vegetation.

2.2 LiDAR data

The original LiDAR data of this study was obtained in October 2016 using a LiDAR scanner system installed on a fixed wing aircraft. LiDAR data type is discrete point cloud data. The density of point cloud in the study area is 2.8 points per square meter. The final LiDAR point cloud is located in the 49 N / WGS - 84 projection coordinate system of UTM area.

After the noise points are removed from the LiDAR data, the point cloud is divided into non ground point and ground point by using terrasolid software. By using ENVI software, the surface points and non surface points are interpolated into 1-m resolution digital surface model (DSM) and digital elevation model (DEM). The difference between them is the canopy height model (CHM) reflecting the height structure information of trees.
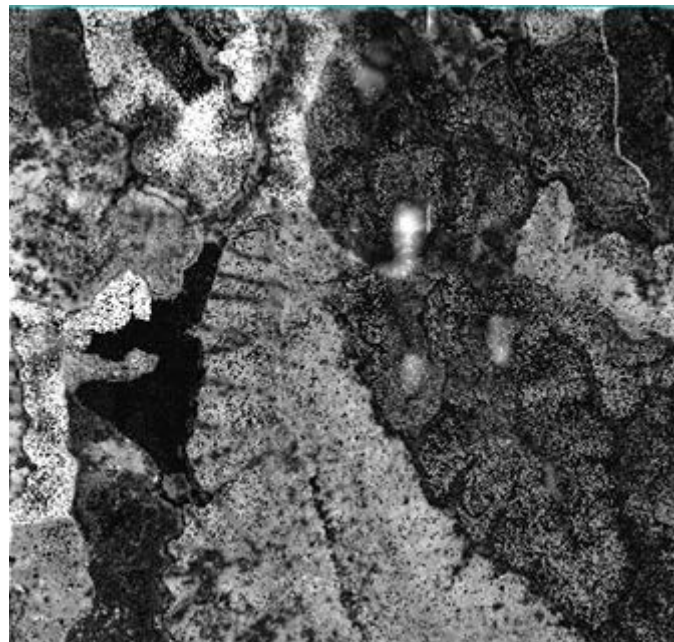

Figure 1. CHM image extracted from laser point cloud data.

2.3 GF-2 satellite and auxiliary data

GF-2 satellite is the first civil optical remote sensing satellite independently developed by China with a spatial resolution better than 1 meter. It is equipped with two high-resolution 1 meter panchromatic and 4 meter multispectral cameras. GF-2 satellite was successfully launched on August 19, 2014, and on August 21, it was turned on imaging and data transmission for the first time.

The detailed payload parameters are shown in Table 1

Table 1. Parameters of payload of GF-2 satellite.

Payload	Band no.	Spectral range (μm)	Spatial resolution (m)	Swath width (km)	Side-looking angle (°)	Repetition cycle (days)
Panchromatic camera	1	0.45–0.90	1	45 (2× Camera stitching width)	±35	5
Multispectral camera	2	0.45–0.52	4			
	3	0.52–0.59				
	4	0.63–0.69				
	5	0.77–0.89				

GF-2 image selected in this paper was shot on May 23, 2018. The image contains 1-m resolution panchromatic and 4-m resolution multispectral bands. In this paper, ENVI software is used to preprocess GF-2 image, such as radiometric calibration, atmospheric correction and ortho correction. At the same time, the 1-m resolution panchromatic and 4-m resolution multispectral images are fused to generate 1-m resolution multispectral images. The CHM image extracted from LiDAR data is used as the reference image for multispectral image registration and resampling after fusion to obtain the total root mean square error of less than 1 pixel. The image is resampled into multispectral images with resolution of 2m and 4m.

2.4 Spectral analysis

According to the resampled multispectral images, the mean and variance of red-green-blue triple band spectra are taken as the spectral characteristics of the subsequent forest classification.

2.5 Texture analysis

The texture feature of image is one of the other key features to identify ground objects. The gray level co-occurrence matrix is a commonly used method to extract texture information. In this study, four gray level co-occurrence matrix texture statistics with small redundancy and high robustness in the red, green and blue band of resampling with GF-2 are selected: angular second moment (ASM), entropy, correlation and contrast .After texture feature analysis, 7 × 7 pixels with the best performance are selected for subsequent classification.

2.6 Structural analysis

The image of the canopy height model (CHM) reflects the structural information of the study area. In this study, the six features of the image of the canopy height model (CHM) are taken as structural feature parameters to participate in the structural feature analysis[11].

2.7 Image segmentation

Image segmentation is an important part of image feature type recognition. In this paper, we use the multi-resolution segmentation with good segmentation effect in eCognition Developer to segment the image. Through the continuous test of segmentation scale segmentation, the final selection of high-resolution fusion image segmentation scale of 2m resolution is 95, high-resolution fusion image segmentation scale of 4m resolution is 60, shape ratio is 0.1, compression ratio is 0.5[12]. The segmentation work of regional remote sensing image is carried out. The segmentation scale can better match the management area of the forest stand (the most suitable management area of the forest stand is about 5 hectares), and can better map out the land, water, sparse forest land and different texture types of forest in the image.

In order to effectively compare the classification accuracy of remote sensing image with the addition of structural features, two segmentation scenarios are used to compare the classification accuracy with the other parameters unchanged: scenario 1: image segmentation based on spectral features and texture features; scenario 2: adding the canopy height model image with structural information as a grid layer to the original different space in the high resolution fusion image, spectral and texture features are combined to participate in the multi-scale segmentation process.

2.8 SVM classification

Compared with pixel based classification, object-oriented classification can make full use of the spectral and spatial information of image, get more information, eliminate the influence of "salt and pepper" noise and improve the accuracy of high-resolution image information extraction[13]. As a machine learning algorithm, SVM classification has perfect theory, sparsity and robustness, which use a small number of samples can get better classification effect. It is one of the commonly used kernel learning machine learning algorithms[14]. In SVM classifier, the kernel function of radial vector is the most widely used. Through experiments, the classification performance is the best when σ is 10.
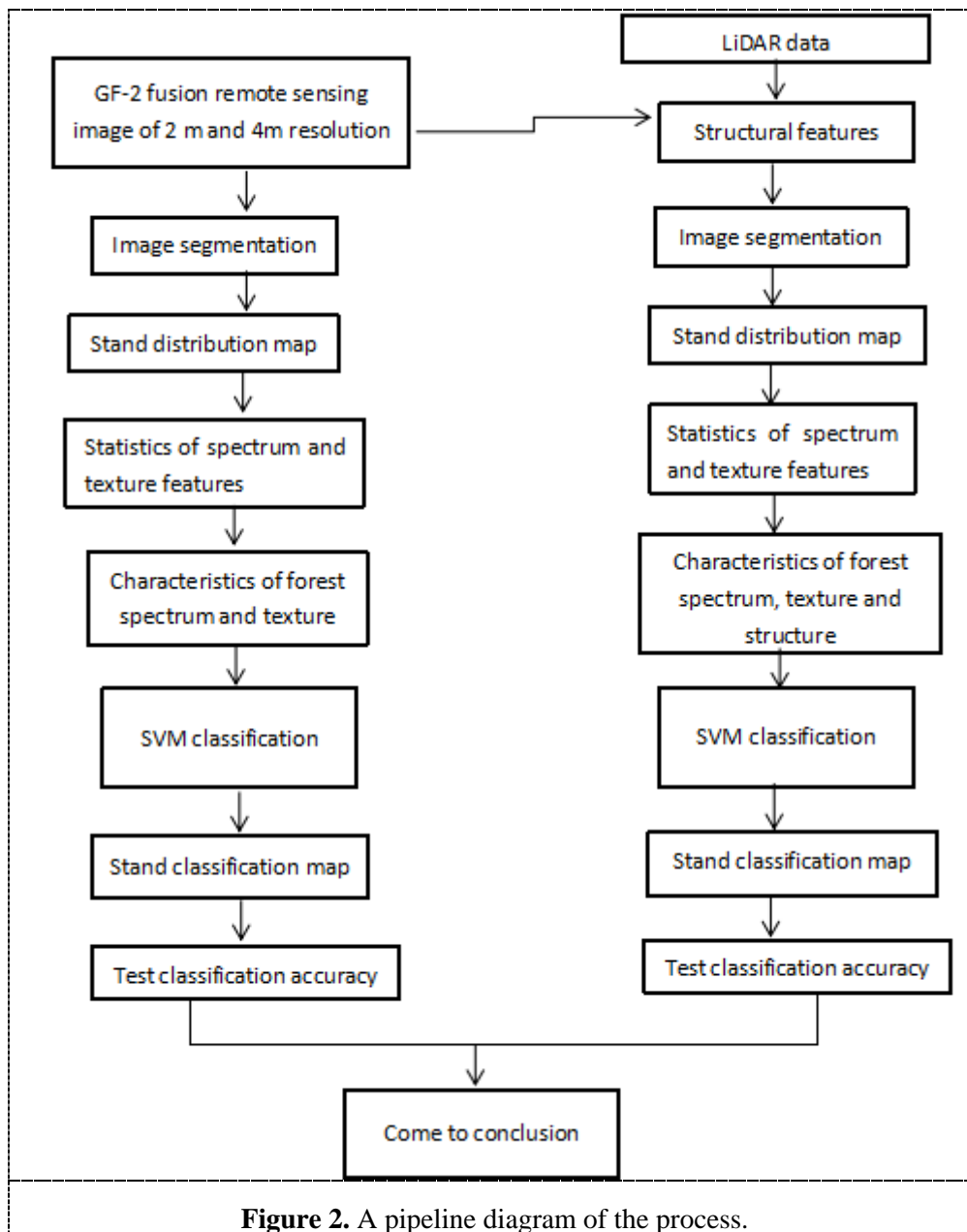
A pipeline diagram of the process is shown in Figure 2.

Figure 2. A pipeline diagram of the process.

Therefore, the SVM classification algorithm of radial vector kernel function (C = 2, σ =10) is selected to train the texture features and spectral features of the B, G and R bands of the samples converted from 23 (half of the number of plots) plots measured on the spot (in scenario 2, in addition to the training of the spectral and texture features of 23 plots, the structural features based on canopy height model image is also required. It is a total of 24 features) . Classifying the GF-2 fusion images at different resolutions of 2 m and 4m, the distribution map of coniferous broad-leaved forest and the distribution map of specific forest species at 2m resolution (see Figure 3-1, 3-3, 3-5, 3-7), the distribution map of coniferous broad-leaved forest and the distribution map of specific forest species at 4m resolution,(see Figure 3-2, 3-4, 3-6, 3-8) are obtained respectively. The confusion matrix of accuracy evaluation for subsequent conclusion analysis are shown on table 2-1 and table 2-2.
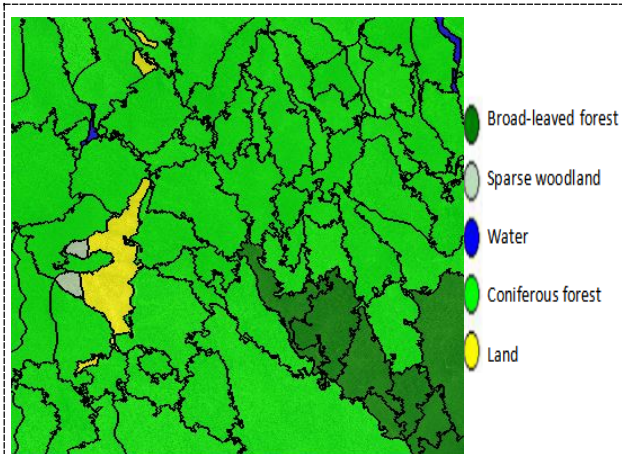
Figure 3-1. classification of coniferous and broad leaved forest using spectral and texture characteristics based on 2m resolution.

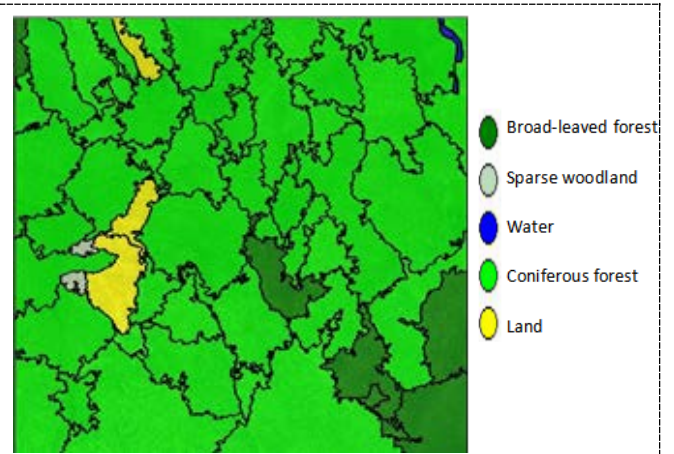**Figure 3-2.** classification of coniferous and broad leaved forest using spectral and texture characteristics based on 4m resolution.
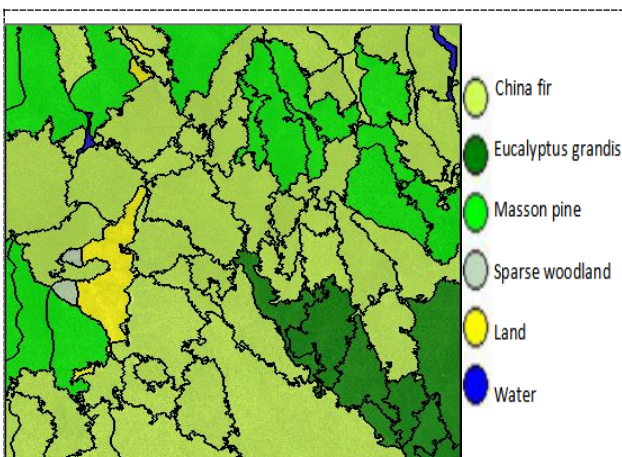

Figure 3-3. classification of specific forest stand species using spectral and texture characteristics based on 2m resolution
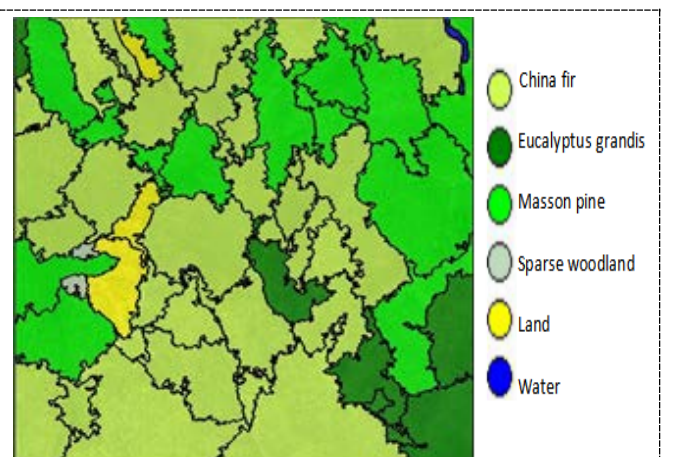

Figure 3-4. classification of specific forest stand species using spectral and texture characteristics based on 4m resolution.
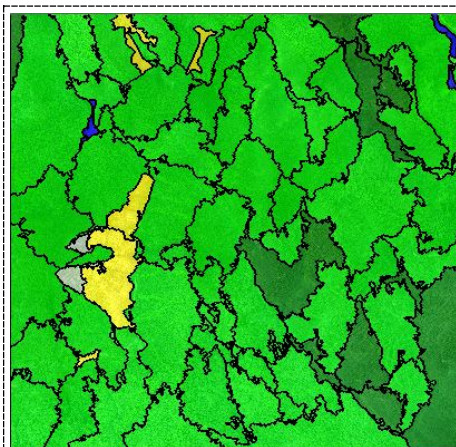
Figure 3-5. classification of coniferous and broad leaved forest using spectral, texture and structure characteristics based on 2m resolution
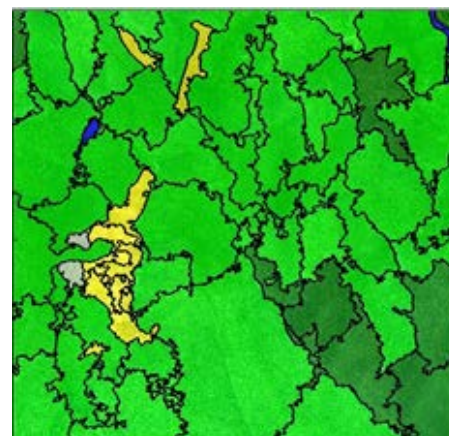
Figure 3-6. classification of coniferous and broad leaved forest using spectral, texture and structure characteristics based on 4m resolution.
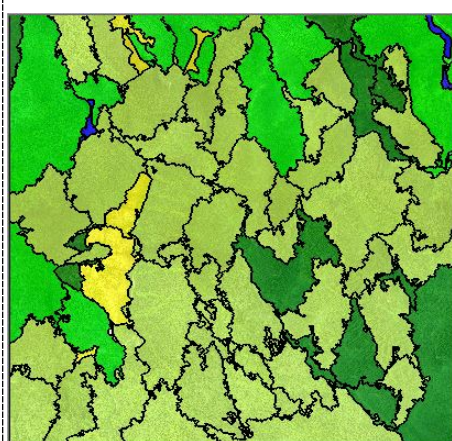
Figure 3-7. classification of specific forest stand species using spectral, texture   and structure characteristics based on 2m resolution
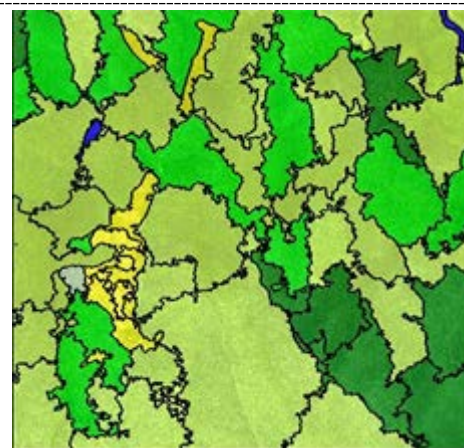
Figure 3-8. classification of specific forest stand species using spectral, texture   and structure characteristics based on 4m resolution

2.9 Accuracy evaluation

In this paper, there are 46 sample data, including geographic location, tree species, coniferous and broad-leaved forest and other information. Among them, 50% of the sample data are randomly selected as the training data of SVM classifier, and the other 50% are used as the test data, and the confusion matrix is obtained to evaluate the accuracy of classification results[15].

3.   Results and evaluation

Table 2-1. classification accuracy of coniferous and broad leaved forest based on GF-2 fusion image of 2 m resolution.

Stand types	Spectral features and texture features				Spectral features, texture features and structural features			
	coniferous forest	broad-leaved forest	PA	UA	coniferous forest	broad-leaved forest	PA	UA
coniferous forest	15	5	1	0.75	15	4	1	0.79
broad-leaved forest	0	3	0.38	1	0	4	0.5	1
	Overall Accuracy : 78.26%				Overall Accuracy : 82.6%			
	Kappa : 0.44				Kappa :0.57			

Table 2-2. classification accuracy of coniferous and broad leaved forest based on GF-2 fusion image of 4m resolution.

Stand types	Spectral features and texture features				Spectral features, texture features and structural features			
	coniferous forest	broad-leaved forest	PA	UA	coniferous forest	broad-leaved forest	PA	UA
coniferous forest	15	5	1	0.75	15	5	1	0.75
broad-leaved forest	0	3	0.38	1	0	3	0.38	1
	Overall Accuracy : 78.26%				Overall Accuracy : 78.26%			
	Kappa : 0.44				Kappa :0.44			

From the classification results, it can be seen that when SVM classification is based on 2m resolution GF-2 fusion image, the classification accuracy of coniferous and broad-leaved forest using the combination of spectrum, texture and structure features is significantly better than that of combining spectrum and texture features (see table 2-1), because the addition of structural features reflected by the canopy height model image extracted from LiDAR data makes up for the insufficient, improves the classification accuracy and increases the separability of feature space. The accuracy of broad-leaved forest producers is higher, from 0.38 to 0.5, which means the classification results are more accurate; the accuracy of coniferous forest users is higher, from 0.75 to 0.79, which means the classification results with higher reliability can be obtained in production and life. The overall

classification accuracy increased from 78.26% to 82.6%, and kappa coefficient increased from 0.44 to 0.57. The overall classification results have higher accuracy and reliability.

When SVM classification is based on 4m resolution GF-2 fusion image, the classification accuracy of coniferous broad-leaved forest using the combination of spectrum, texture and structure features is not much different from that using the combination of spectrum and texture features (see Table 3-2). When the resolution of the target image is low, the structural features have little effect on improving the classification results.

By comparing table 3-1 with table 3-2, it can be concluded that compared with GF-2 fusion of 4m, GF-2 fusion image of 2m has clearer detail expression and richer image presentation information. The overall classification accuracy (total classification accuracy) and reliability (kappa coefficient) of the 2m resolution fusion image is higher than that of the 4m, which is consistent with our prior knowledge.

Table 2-3. classification accuracy of specific forest species based on 2m resolution GF-2 fusion image.

Stand types	Spectral features and texture features					Spectral features, texture features and structural features				
	Masson pine	China fir	Eucalyptus grandis	PA	UA	Masson pine	China fir	Eucalyptus grandis	PA	UA
Masson pine	4	0	1	0.8	0.8	5	0	1	1	0.83
China fir	1	10	3	1	0.71	0	10	0	1	1
Eucalyptus grandis	0	0	4	0.5	1	0	0	7	0.88	1
	Overall Accuracy :78.26%					Overall Accuracy :95.65%				
	Kappa : 0.65					Kappa : 0.93				

Table 2-4. classification accuracy of specific forest species based on 4m resolution GF-2 fusion image

Stand types	Spectral features and texture features					Spectral features, texture features and structural features				
	Masson pine	China fir	Eucalyptus grandis	PA	UA	Masson pine	China fir	Eucalyptus grandis	PA	UA
Masson pine	1	0	2	0.2	0.33	2	0	2	0.4	0.5
China fir	4	10	3	1	0.59	3	10	3	1	0.63
Eucalyptus grandis	0	0	3	0.38	1	0	0	3	0.38	1
	Overall Accuracy :60.87%					Overall Accuracy :65.22%				
	Kappa : 0.35					Kappa : 0.43				

When using spectral, texture and structural features to classify specific forest species with GF-2

fusion image of 2m resolution, the classification accuracy and reliability are significantly improved (see table 3-3), the total classification accuracy is increased from 78.26% to 95.65%, and the kappa coefficient is increased from 0.65 to 0.93, which has a very strong accuracy. The user accuracy of Pinus massoniana and Cunninghamia lanceolata increased from 0.8 to 0.83 and from 0.71 to 1 respectively, which means the classification result more accurate; the producer accuracy of Eucalyptus grandis also increased from 0.5 to 0.88, which made it more reliable. At the same time, using spectral, texture and structural features to classify specific forest species with GF-2 fusion image of 2m resolution, the classification effect is better and it is more suitable for daily production research and practical application.

When the spectral, texture and structural features are used to classify the specific forest species in the 4m resolution GF-2 fusion image, the classification accuracy and reliability are slightly improved compared with the spectral and texture features (see table 3-4).The total classification accuracy is increased from 60.87% to 65.22%, the kappa coefficient is increased from 0.35 to 0.43 and the user accuracy of Masson Pine and Chinese fir is also increased from 0.33 to 0.5 and from 0.59 to 0.63 respectively, which means classification result is more accurate.The producer precision of Pinus massoniana is improved from 0.2 to 0.4, which is more reliable.

Compared with the coniferous and broad-leaved forest classification based on remote sensing images, the addition of structural features plays a more important role in improving the classification accuracy. The classification effect of GF-2 fusion image with 4 m resolution is significantly lower than that of high-resolution fusion image with 2 m resolution, which is closely related to the lower image detail presentation of GF-2 fusion image with 4 m resolution, and also consistent with our prior knowledge.

4. Conclusion and discussion

According to the analysis of the results of this study, the following conclusions are obtained:

1.Combining the spatial structure information extracted from LiDAR data with the spectral and texture features extracted from multispectral remote sensing data for forest type recognition, the recognition effect is better, the accuracy and reliability are higher and the separability of feature space is increased.

2.The GF-2 fusion image with 4m spatial resolution has poor detail performance. Under the condition of using the same classification features and classification algorithm, the classification effect of forest type is far less than that of GF-2 fusion image with 2m spatial resolution and has low reliability. Therefore, if the conditions permit, the satellite remote sensing image with higher resolution should be selected as much as possible, which will help to improve the classification accuracy and reliability of classification results.

3.Due to the influence of SVM classifier and selected spectrum, texture and structure classification features, the classification effect of specific tree species is better than that of coniferous broad-leaved forest. It may be because the spectrum, texture and tree height features of specific tree species are more specific and accurate, and easier to distinguish in detail, which lays a theoretical and practical foundation for the detailed classification of future tree species.

4.According to the research methods in this paper, we can get high recognition accuracy for forest type recognition. And compared with the the required professionalism, the current manual supervision

classification's efficiency is higher, which is more suitable for the future forest type recognition work in a wide range of promotion and application.

Although LiDAR data combined with high-resolution remote sensing data are applied to forest type recognition in the study area, some progress has been made in improving the accuracy of forest type recognition, and some conclusions are obtained which can be applied to future forest type recognition. However, there are still some problems to be improved and further explored in the future research and learning, mainly including the following two points:

1. At present, airborne LiDAR data used for forest type recognition are mainly divided into two categories: full waveform and discrete point cloud data. The full waveform LiDAR data has large facula and low density. By recording complete echo information, it can provide echo intensity, waveform and pulse width information for forest tree species classification. The scattered point cloud data has small spot and high density. Through the electromagnetic wave to the forest surface, the echo signal above the canopy and the terrain surface is used to obtain and construct the canopy height model (CHM) of the canopy, so as to obtain more spatial structure information such as the three-dimensional spatial structure of trees. In the future research, we can combine different types of LiDAR data, spectrum and texture information to select more accurate and efficient parameters for forest classification.

2. SVM classifier algorithm is a machine learning algorithm. By continuously optimizing training samples and selecting training features, more accurate classification results can be obtained. How to further train and optimize SVM classifier to improve its classification accuracy and reliability, and how to compare with other machine learning algorithm classification results, further research work is needed.

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