Research Dynamics of the Classification Methods of Remote Sensing Images

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Abstract As the key technology of extracting remote sensing information, the classification of remote sensing images has always been the research focus in the field of remote sensing. The paper introduces the classification process and system of remote sensing images. According to the recent research status of domestic and international remote sensing classification methods, the new study dynamics of remote sensing classification, such as artificial neural networks, support vector machine, active learning and ensemble multi-classifiers, were introduced, providing references for the automatic and intelligent development of remote sensing images classification.
Key words Remote sensing images, Classification methods, Classifiers

The extraction of remote sensing (RS) information has always been a tough problem. With the increasing amount of high spatial resolution RS data, it has become a scientific issue about how to comprehensively use various information extraction techniques and integrate the results of multi-scale information extraction for the better and quantitative information extraction from RS data[1-2]. The key of RS information extraction lies in the classification and identification of image objects.

The classification of RS images means to classify the pixels by certain rules or algorithms according to their spectral signatures, spatial structure or other information[3]. The classification results are influenced by the complexity of ground studied, the RS data selected, as well as the image processing and classification methods. Affected by various factors, the RS classification has always received much attention of researchers[4], who have carried out lots of studies on the techniques and evaluation of classification performance[5-7].

1 Introduction to the classification of RS images

The classification of RS images is a complicated process, which practically involves several steps as shown in Fig. 1.

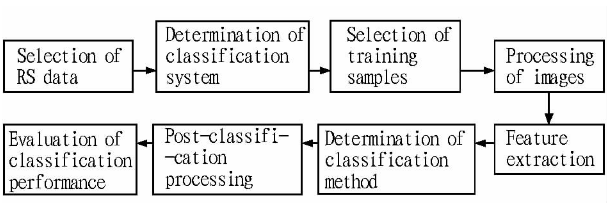

Fig. 1 The classification process of RS images

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During the data processing, the classification can't be successful without an appropriate classification method. The classification methods belong to different classification systems, which are briefly described by Lu: the classification systems can be classified into supervised and unsupervised systems based on their needs for training samples or not. The supervised classification system includes the methods of linear discriminant, maximum likelihood classifier, minimum distance, artificial neural network, Mahalanobis distance, and Parallelepiped; while the unsupervised system includes the methods of ISODATA and K-Means cluster; According to their use of parameters, the classification methods are classified into the parameter classification and non-parameter classification, the former includes the methods of linear discriminant and maximum likelihood; while the latter includes the methods of artificial neural network, decision tree, support vector machine and expert system; According to which kind of pixel information is used, the classification methods are divided into the pixel-based, sub-pixel-based and object-based types, the pixel-based classification methods include the maximum likelihood, the minimum distance, artificial neural network, decision tree and SVM; while the sub-pixel-based classification methods include the fuzzy set, mixed spectral classification, the object-based classification is adopted in the eCognition software; Based on whether output is a definitive decision or not, the methods are categorized into the hard classification and soft classification, the former one refers to the maximum likelihood, the minimum distance, artificial neural network, decision tree and SVM; while the latter one refers to the fuzzy set classification and mixed spectral classification[4].

2 New techniques of RS images classification

2.1 Neural network classifier With the development of artificial neural network theory, the neural network technique has become an effective means to process RS images. Various forms of neural networks have been developed by the researchers both at home and abroad, including the back-propagation network, fuzzy neural network, multi-layer perception network, Kohonen self-organizing feature map, Hybrid learning vector hierarchial network, Hopfield network and ART (Adaptive Resonance Theory) model, and so on. The neural network has been widely adopted in the classification of RS images[8-9]. Given that the RS classification by neural network relies on both the quality and quantity of training samples, it has several problems, such as the slow convergence speed, falling into local minima and unstable network memory. Qian Yao adopted the genetic algorithm to optimize LVQ neural network for RS classification[10]; Xue Wan employed the improved RFB neural network algorithm to the classification of high resolution RS images[11]. The research of ANN focuses on the selection of appropriate network structure (the optimal number of hidden layers and hidden nodes) and training rules, so as to obtain better classification results. Nowadays, the combination of ANN with other theories and techniques, including expert system, fuzzy mathematics, evolutionary algorithm, images fusion technique, and geoscience knowledge, has become one of the focus of RS classification study[12]. The fuzzy set theory and fuzzy neural network realize the effective classification and recognition of RS images objects[13]. ANN is combined with geoscience knowledge and images fusion technique to improve the precision and speed of RS classification[14]. Xusheng Liu well classified the RS images of forest vegetation by the BP neural network with the Landsat 7 ETM + RS data and forest resources distribution map[15].

2.2 SVM As a type of machine learning algorithm based on statistical learning theory, the SVM seeks to find out the optimal separating hyperplane from the high-dimension feature space so as to solve the classification problems of complex data. The SVM technique has been widely used in the classification of RS images because of its convenience, stability and high precision[16]. SVM, in comparison with the maximum likelihood method, neural network and decision tree, is much more stable in its precision and can use smaller training data set and high-dimension space data[17]. Based on the traditional classification, Zhong Chen proposed a multiple classifier system with a mixed combining rule for decision not a single rule to improve the classification accuracy, and applied SVM to the high resolution RS images classification. [18].

One of the key factors influencing the performance of SVM method lies in the selection of kernel functions, which determine different non-linear transformation and feature spaces, as well as influence the classification accuracy. Thus, the kernel functions should be reasonably selected, improved and optimized, and they are now commonly selected and optimized by the genetic algorithm and immune genetic algorithm in practical application.

SVM itself can only be used for binary classification, and the common multi-classification methods include the OAO, OAA and DAG methods. The studies about SVM multiclass classification strategies are now in progress. Hsu proposed a "one-shot" strategy, which searches to solve the problem of complex optimization and integrate multiclass classification into one SVM[19]. Melgani used two multiclass strategies of BHT-BB and BHT-OAA based on the binary tree, and improved the speed of multiclass classification but reduced the cumulative error of integrating multiclass classification[20]. Chen introduced the dual decision tree into the SVM and proposed that the solving time of new multiclass strategy was $(N-1)$, while that of OAO was $N(N-1)/2$. The times of calculation is reduced and the efficiency is improved[21].

According to the multisensor and multi-temporal data, as well as the high-dimensional space classification of SVM, the studies on the combination of data infusion and SVM have achieved great process. Waske integrated the SAR, Landsat TM and SPOT data for the decision classification of SVMs, and gained a classification result which had higher accuracy than that of any single data source[22]. The classification of high space resolution RS images based on the multi-source information integration of SVM[23] has achieved good result. Lingmin He studied the selection of support vector machine in RS images classification model, including the selection of multiclass model and kernel functions; she also combined the geography-aided data with the vegetation index and spectral data, which was proven by results to have greatly improved the accuracy of multi-source land use/cover classification based on support vector machine[24].

The researchers put their focus on improving both the accuracy and speed of SVM classification, and new SVM classification algorithms keep arising. According to Bayesian minimum error decision method, Mantero introduced the SVM into the estimation of probability density and proposed to apply it to the classification of RS images under limited ground reference data[25]. Bruzzon introduced the transductive learning into the SVM RS images classification, and incorporated both labeled and unlabeled samples in the training phase. In the experiment of TM images classification, the results had higher precision than that of traditional SVM classification[26]. Castillo proposed Boostrapped SVM, and removed the inaccurate training samples from the training set, and then redistributed the new labels and added them into the next loop of training set[27]. Demir classified the high-spectral RS images by the related vector machine, which reduced the calculation amount and improved the classification speed[28]. In addition, the studies aiming at decreasing sample data and improving the reliability of training have also received much attention[29].

The SVM study has always focused on the construction of kernel functions, the selection of parameters, the multiclass strategies, the optimization of algorithm and the improvement of SVM constraints, while the further study of these issues will also be beneficial to effectively transform the RS data into useful information[30].

2.3 Active learning With the very few labeled training samples and a number of unlabeled data in the classification of RS images, it has become a hot topic about how to use the large amount of unlabeled samples for learning and improve the classification performance.

The traditional supervised learning is based on the labeled sample set and induces a model for separation. In practical application, it is quite difficult and time-consuming to label samples. While the active learning, as a new method of sample training, is completely different from the passive learning method based on randomly selected samples, its learner selects and then labels some representative data as training samples. The method is guided respectively by the learning and selection acting, which gradually improves the performance of base classifier after several times of loop[31]. The active learning has received a wide attention because of its applicability in RS images classification[32-34]. Jianjie Chen proposed a new active learning method based on the multiclass Classification SVM, which, based on the initial training set with few labeled samples, finds out the best samples for SVM classifier as the support vector by the means of iterative active learning[29].

The semi-supervised classification technique, as a present research focus of machine learning, is the mainstream learning method exploiting the unlabeled samples[35]. By introducing a large number of unlabeled samples, the accuracy of classification is greatly improved, and thus the objects can be much more easily recognized[36-38]. Based on self-training, co-training and low-density separation, Wei Yang built initial classifiers using labeled samples, then improved themselves using unlabeled samples recursively. The results showed that it could get higher accuracy than that based on supervised learning[36]. Considering the SAR images with limited quantity of labeled samples, Rong Chen proposed a method Best vs second-best (BvSB) active learning to explore examples that are the most valuable to current classifier model for labeling, built a better initial training set, and carried out semi-supervised training by the constrained self-training (CST), which effectively reduced the quantity of labeled samples needed for classifier training, and gained higher accuracy and better robustness[37].

2.4 Multi-classifier ensemble The studies have proven that there is no one best classifier for all classification problems, thus it is difficult to find the best classifier, and the classification performance of single classifier cannot be effectively upgraded[5]. The existing classification algorithms are combined together with appropriate methods to improve the classification precision of RS images by the complement of different classifiers. The research and application of ensemble learning technique has become one of the research focus of current RS classification. As a model of machine learning, the ensemble learning can obtain different types of classifiers and then combine them together according to certain rules to solve one problem, which can effectively improve the generalization of the learning system. Three steps are involved in the design of the ensemble learning method: first, the generation of base classifiers. The different base classifiers are trained on different training data subset which are produced through the processing of original data set. Second, the selection of base classifiers. The optimal classifiers are selected according to certain rules for ensemble classification. Third, the ensemble of base classifiers.

The present studies of multi-classifier ensemble mainly focus on above three aspects. Boosting and Bagging are the most commonly used ensemble methods. Hatami trained the different classifiers by the Boosting method and combined the classifiers by the Stacking method, which greatly improved the classification accuracy[39]. However, the over-emphasis of samples will lead to the situation of over-fitting and the sensitivity to noise. Random Forest (RF), a classification and prediction model proposed by Breiman in 2001, is composed of several decision trees, which jointly determine the classification results. Several samples are extracted out from the original samples by bootstrap method, and a model is built for the decision tree of every bootstrap sample subset, and finally the results of several decision trees are integrated using voting to obtain the final classification. The RF has achieved high accuracy of classification in application of RS image[40-42].

Yanchen Bo carried out a study of RS classification by using the multi-classifier ensemble method based on multiple standards[43]. Zhenglin Peng selected the three classifiers of Mahalanobis distance, SVM and Maximum Likelihood as the sub-classifiers, and combined them with the simple voting, maximum probability classification method and fuzzy integral method according to custom rules, which greatly improved the overall classification accuracy[44]. Chungan Li proposed three multiclassifier combination methods, include voting rule, Bayesian mean and fuzzy fusion rule, a new fusion approach named voting-fuzzy rule was developed, which synthesized conservative voting rule and fuzzy fusion rule, whose classification results are greatly improved than that of single classifier[45]. Yongcong Ma designed two multi-classifier ensemble models by the genetic algorithm[46]. Haibo Yang proposed a hybrid multi-classification algorithm based on the optimal subclassifier, Bagging algorithm and maximum confidence interval[47].

The multi-classifier combination refers to improve the recognition performance with large quantity of base classifiers and still has several problems, for example, firstly, the use of many classifiers will result in large costs of calculation and storage; secondly, the difference among the classifiers will be decreased with the increasing number of base classifiers. Thus, how to select the optimal one from so many classifiers has become a tough problem, and the researchers should study the diversity measurement of classifiers[48-49]. It is hoped to find out the associated metrics of certain classifiers to ensemble the multi-classifier system.

2.5 Contextual classifications The classification based on the contextual information means to improve the classification results based on the spatial information between pixels by the Markov Random Fields (MRF), spatial statistics, fuzzy logics and neural network technique[50]. The method added the contextual information into traditional classification method as additional waveband. The contextual classifiers based on MRF model is commonly used, which can effectively enhance the classification accuracy[51]. Hui Zhou proposed to ensemble the multi-layer contextual information for the classification of high-resolution RS images, and the contextual information was used at three stages from simple part to complex global, which gradually improved the classification results and realized the high-resolution objects classification[52].

The existing classifiers are mostly proposed for the classification of pixels, while the pixels and objects are different in both their size and contents, especially in their information, so how to construct a high-efficient semantic classifier with the contextual information still needs to be further studied.

3 Research trend of RS images classification methods

The classification of RS images is not only a key technique of RS images interpretation, but also an important research direction in the field of remote sensing. In recent years, the RS classification mainly develops in two directions. Firstly, new RS classification methods, such as neural network, support vector machine, fuzzy set theory, immune algorithm[53], *etc.*, are proposed and constructed; secondly, diverse classifiers are integrated and combined. Nowadays, the research of RS images classification methods mainly focuses on the following aspects: firstly, the machine learning algorithm is combined with the RS classification, active learning, semi-supervised learning, ensemble learning technique and traditional RS classification methods, and the existing algorithm or related new algorithms are continuously improved so as to improve the classification efficiency, learning speed and generalization of RS images classification; secondly, according to practical application, the geographical information, together with the GIS and multi-source RS data combination, should be carefully studied so as to realize the classification of high-resolution images; thirdly, the ensemble of multi-classifier has achieved good classification results through the ensemble learning technique and the complementary information of each base classifier. But how to obtain the base classifiers with great difference, and evaluate their difference as well as the ensemble of each base classifiers still need to be further studied.

4 Conclusion

As the sensor technique, aeronautic and astronautic technique, and data communication technique develop rapidly, modern RS technology has been uplifted to a new stage of dynamic, rapid, multi-platform, multi-phase and high-resolution earth observation. The application of RS technology has been further expanded, the RS information is becoming richer and richer, and the requirements for the precision of RS classification are gradually improving, thus, the traditional classification method cannot meet the requirements for classification accuracy. The theory and methods of artificial intelligent, pattern recognition and machine learning are improved, and new methods and technology continue to arise, which all provide a wide space for the research of intelligent and high-resolution RS classification methods.

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(From page 117)

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