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A Survey on Classification Techniques used in Remote Sensing Data

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Abstract:
Purpose of the present paper is aimed at the classification of remote sensing application. This survey provides the overview of classification techniques in agricultural land value classification integrated in the land consolidation survey, land use change mapping and analysis, discovery of risk areas, regional crop rotation mapping, vegetation dynamics based on time series Land sat image for all related recent remote sensing classification techniques.

Keywords: Decision Tree (DT), Markov Random Field (MRF), Maximum Likelihood (ML), Object-oriented classification, Random Forest (RF), Support Vector Machine (SVM)

I. INTRODUCTION

The number of satellite missions dedicated to remote sensing or Earth Observation(EO) has increased significantly over the past decade and will further increase over the coming decade and beyond. Data from these missions offer the potential for contributing to the security of human existence on Earth in different ways. Although there have been many demonstrations of the value of EO satellites to development issuses such as food production, resource management and environment characterization, it is recognized that there is a role for transferring that knowledge to developing countries. In remote sensing data, higher resolution images have guaranteed better land cover. The image classification techniques used a very important factor for better accuracy. Classification is one of the data analysis tasks. In this research, the process of finding a model that describes and distinguishes data classes and concepts. Three types of image classification used in remote sensing data are: Unsupervised image classification, supervised image classification, object-oriented classification. Under the each classification so many classifiers are existed to explore the better accuracy. The present paper contributes to the classification methodology development for the remote sensing application over the past recent few years.

II. OVERVIEW OF CLASSIFICATION

Jing Wang et al, [1] explored the object-oriented information extraction method to extract aquatic approach for high resolution image (GeoEye-1). Taken nature reserve wetland BaiYangDian for analyzing spectral characteristics and study optimal combination bands model, constructed the classification of acquatic plants extraction decision, classified by object-oriented classification method. This work has provided technical support in the wetland vegetation interpretation and vegetation dynamic distribution. Here the experimental results has proved that the object-oriented classification based on spectral information has greatly improved with the traditional pixel-based classification method. FEI LV et al, [2] demonstrated a remote sensing image classification algorithms based on the ensemble of Extreme Learning Machine (ELM) is proposed to solve the problem of poor data classification and low classification efficiency due to the complex data type and the small number of training samples in classifying remote sensing images. The algorithm firstly segments the features in the original training set, and then transforms the segmented sub-features for classification to improve variance among the base classifiers. Then transformed training set to train each ELM base classifier, and finally use a statistics to measure the difference between base classifier and the classifier with greater difference is selected to synthesize the results and to obtain the final classification results. According to the classification experiment results on the remote sensing images for Zhalong wetland, a certain development zone, Haicheng River and Indian pines, compared with other ensemble algorithms, the proposed algorithm has higher classification accuracy and stronger generalization performance and can adapt to the classification of different resolutions and hyper spectral remote sensing images. The main drawback of this paper is the manual selection of the number of base classifier for Q-Statistics. Xue Li et al,[3] explored transfer learning method. It can adapt knowledge to the existing images to solve the classification problem in new yet related images, and have drawn increasing interest in the remote sensing field. The existing methods in the RS field require that all the images share the same dimensionality, which prevents their practical application. This technology focus on the transfer learning problem for heterogeneous spaces where the dimensions are different. This work proposed a novel iterative reweighting heterogeneous transfer learning (IRHTL) framework that iteratively learns a common space for the source and target data and conducts a novel iterative reweighting strategy to reweight the source samples. In each iteration, the heterogeneous data are first mapped into a common space by two projection function based on a weighted support vector machine. Second, based on the common subspace, the source data are reweighted by using the iterative reweighting strategy and reused for the transferring according to their relative importance. Experiments undertaken on three data sets, Pavia data set, the Washington DC mall data set and the urban data set located at Copperas Cover near Fort Hood, USA confirmed the effectiveness and reliability of proposed IRHTL method. Here, images from the first two data set were used as the source domains, while the third data set was used as the target domains. Two experiments on the three real world hyper spectral data set confirm that the proposed IRHTL method is able to solve the heterogeneous TL problem in remote sensing image classification by transferring knowledge between heterogeneous hyperspectral data. IRHTL can perform well for the major land-cover classification when the source and target images have different dimensions, captured by a same sensor or different sensors, in different locations and or at different times.

The training learning method performans better than all the comparison methods including SVM-T, ARC-t, CCA+SVM and HFA. The proposed method can effectively improve the classification accuracy by using heterogeneous source samples in the case of limited labeled target samples. IRHTL can perform well for the major land-cover classification captured by a same sensor or different sensors in different locations and or at different times. The overall accuracy is 91.60% by the use of different numbers of labeled target and source samples. In recent years, Level Set Evolution-LSE has been shown to be very promising for object extraction in the field of image processing because it can handle topological changes automatically while achieving high accuracy. Zhongbin Li [4], proposed two fast LSEs: edge-based LSE and region-based LSE for the extraction of man-made object from high spatial resolution remote sensing images. Compared with state-of-the-art LSEs in extracting building roofs, road networks, airport runways, the proposed LSEs are computationally much more efficient while achieving better performance. The main limitations of this LSEs are two-fold. First, they require human interaction to set the initial ZLC, which means that they are a semiautomatic method. The future-research can be directed at extraction of natural objects such as tree crown, water-body, agriculture mapping. That work replaced the traditional mean curvature based regularization term by a Gaussian Kernal, and it is mathematically sound to do that. Thus larger time step in the numerical scheme to expedite the proposed LSEs. Compared with existing methods, this LSEs are significantly faster. Traditional LSEs can be further improved both in terms of parameter tuning and computational efficiency.

Crop identification and mapping is the need of the today's world. The most important activities include identifying the crop types and depict their extent. The efficiency and accuracy of data were improved when remote sensing data products and GIS are used. Pushpak Teredesai et al, [5] the input satellite image is used to geo-reference that is mapping of co-ordinates to the image. Then after this, taken the control points during geo-referencing to reference the image with original geographical location. This geo- referenced image then sent in .tiff format to serve as input to digitization. In digitization, different datasets of the image based on type of data created and classify different information layers by converting the raster layer into vector layer. Using this, agricultural map was prepared. Here the implementation of the system based on decision tree learning algorithm used to decide the measures to identify the crops. The assessment result of agricultural land was grouped into classes using manual classification of crops. User can get information about crop such as yield production, collecting crop production statistics, facilitating crop rotation records, mapping soil productivity, assessment of crop damage due to storms and drought and monitoring farming activities. This system builded up a farmland geography information system of Karnataka and the model of variable-rate based on the farm crop yield, improve agricultural product quality, boost agricultural product market competition ability and enhance fertilizer utilization. Jiaxing Xu et al, [6] generated a comprehensive clustering and pixel classification method for extracting the vegetation dynamics based on time series Landsat Normalized Difference Vegetation Index-NDVI. Here the time-division algorithm used for fitting time series NDVI firstly. And then Markov Random Field optimized semi-supervised Dynamic Time Wrapping –Kernel fuzzy C-means clustering was constructed. The MRF optimized semi-supervised DTW- kernel fuzzy C-means clustering was combined with the 1-Nearest Neighbor [1NN], DTW pixel classification to realize the extraction of vegetation dynamics. Compared with other clustering or pixel-classification methods, it achieved high classification accuracy in the mechanism of coal resource exploitation on the vegetation change in Shengli coal mining area. Wanying Song et al,[7] MRF is skillful in incorporating the spatial-contextual information of images and has been widely applied to remote sensing image classification and segmentation. However, the traditional MRF based method is unable to determine the precise number of clusters automatically. It is known that the Dirichlet process mixture model (DPMM) takes the number of clusters as a model parameter and estimates it in image classification. Therefore, the DPMM is a powerful and potential method for classification tasks. Then by fusing the DPMM model and a similarity measure scheme into MRF framework, we propose a novel unsupervised classification and segmentation method for polarimetric synthetic aperture radar (PoISAR) images, abbreviated as DPMM-SMMRF. First, the DPMM built by the multi-dimensional Gaussian distribution is introduced into the MRF framework, which enables the proposed DPMM model to identify the underlying number of clusters automatically. Second, to utilize the polarization information adequately and modulate the spatial correlation, the similarity measure between the neighboring polarimetric covariance matrices is utilized to construct the interaction. Then, for updating the class labels and the parameter in the proposed DPMM-SMMRF model, we propose a detailed sampling procedure based on the Gibbs sampling. Experiments on real PoISAR images demonstrate that the proposed DPMM-SMMRF model can automatically recognize the number of clusters and simultaneously obtain higher classification accuracy, more edge location and smoother homogeneous areas compared to several recent MRF models. Experimental results have shown that the DPMM-SMMRF model provides lighter polluted classification maps and keeps better edge locations at the same time. Most of all, it can recognize the number in real PoISAR images of itself with the absence of prior knowledge. Since the DPMM is suitable for handling classification and segmentation problems, it is meaningful to introduce it into the TMF to estimate the implying nonstationary in PoISAR images, which is becoming a hotspot nowadays. Additionally, two key parameters are tuned by experience, which needs a further study to determine them automatically. Balance parameter λ determines ^{the} power force of the proposed DPMM-SMMRF model, that is similarity measure information in the four-neighborhood system. Concentration parameter and also plays an important role in determining the number of clusters. This DPMM-SMMRF model is tested against the supervised MRF model and the unsupervised MDP/MRF model. Overall accuracy is 93.36% and kappa--coefficient is 0.9080 on “flevoland” PoISAR image. Guido Waldhoff et al, [8] the study has proven that through the integration of remote sensing and GIS methods with our multi-data approach very complex spatio-temporal patterns, in this case for arable land, can be captured at a very high spatial resolution and for a regional scale. Through our combination of multitemporal data, ancillary information and expert-knowledge on crop phenology in a sequential analysis crop types can be accurately even with multispectral data. Here the identification of major crop rotation was focused. The maximum Likelihood method used because of significantly lesser computation time. The annual multi-temporal crop type mapping was classified individually using the supervised pixel-based classification methods MLC. However, a comprehensive analysis to identify all occurring rotations was out of the scope. Amna Butt et al, [9] used supervised classification maximum likelihood algorithm in ERDAS imagine to detect land cover/land use observed in Simly Watershed, Pakistan using multispectral satellite data obtained form Landsat5 and SPOT5. The watershed was classified into five major land cover/land use classes: agriculture, bare soils/ rocks settlements, vegetation and water. Resultant land cover/land use and overlay maps generated in ArcGIS10 indicated a significant shift from vegetation and water cover to agriculture, bare soil/rock and settlements cover, which shrank by 38.2% and 74.3% respectively. These transformations posed a serious threat to watershed resources. For the accuracy assessment of land cover maps extracted from satellite images, stratified random method was used to represent different land cover classes of area. Post-classification refinement was used to improve the classification accuracy and reduction of mis-classification. Boukaye Boubacar Traore et al, [10] the discretization in the preprocessing phase improving the quality of the obtained results, establishment of the link between the environment and the epidemic and identification of most risky areas for the propagation and emergence of the epidemic in the area of choiera epidemic in Mopti region, Mali, west Africa. They used three steps to discretize the remote sensing data: (i) making a decision table (ii) break point and equivalent class (iii) finally run the discretization algorithm [KNN]. Here the supervised classification algorithm maximum likelihood used to generate a map with each pixel assigned to epidemic risk class or not epidemic risk class based on its multispectral composition. Jiahui Li et al,[11] investigated the utility of multisource remote sensing imagery based on wavelet transform(WT) for coastal coverage classification. Multipolarization features with the exception of the normalized radar cross section (NRCS) of four polarization channels. Processing consisted of radiometric calibration, map projection, generation of the multilook covariance matrix C. Imagery fusion method based on WT is widely used for imagery fusion through the multiresolution analysis of the spatial frequency domain. The main idea of WT fusion involves retrieving multiresolution signals from WT and then fusing the images at different scales. Using the maximum likelihood classification (MLC) we achieve high classification accuracy which relies on the Bayesian maximum likelihood approach that discriminates different classes with the same a priori occurrence probabililty. The computation of WT from a 2d image involves recursive filtering and subsampling. The 2D WT will have a pyramid structure. Hongzhou Bay is a representative wetland area located south of the Yangtze river delta, with a winding shoreline and numerous islands. Three scenes of ALOS-2 SAR imagery were collected including two scenes from quad-polarized imagery and one scene from dual-polarized imagery. Two sentine-1 SAR imagery scenes were collected for comparison. Sentinel-1 is the first of the copericus programme satellite constellation launched by the European space agency. Xin Huang et al,[12] proposed two-level machine learning framework for identifying the water types from urban high-resolution remote sensing images. The framework consists of two interpretation levels: (I) Water bodies are extracted at the pixel level, where the water/shadow/vegetation indexes are considered. (II) Water types are further identified at the object level, where a set of geometrical and textual features are used. Both levels employ machine learning for the image interpretation. The method validated using GeoEye-1 and worldview-2 images over tow mega cities: Wuhan and Shenzhen in chinia. The experimental results show that the proposed method achieved satisfactory accuracies for both water extraction 95.4% in Shenzhen and 96.2% in Wuhan and water type classification 94.1% in Shenzhan and 95.9% in Wuhan in the complex urban areas. In the pixel-level for water extraction, the combination of the water, shadow and vegetation indexes makes it possible to effectively extract the water areas from urban high-resolution imagery. The result obtained by the machine learning as the preliminary water layer and input into the object-level for further identifying the water body types. Although the combination of water, vegetation and shadow indexes can effectively extract water surface, it may fail to discriminate between various water types. Consequently, to consider the geometrical and textural attributes of each water body at the object level for the type identification. The proposed processing flow includes the following steps: segmentation, feature extraction, machine learning for classification of water types. The machine learning methods considered here refer to the series of sate-of-the-art algorithms. Decision tree methods-RF and TB achieved the optimal results in terms of both quantitative accuracy scores and visual inspection, particularly siginificantly outperforming SVM and ELM. Object-based geometrical and textural features are rather effective for discriminating between different water types. Consequently, the decision-tree methods which directly consider the original features or their combinations for classifications, give better results than the SVM, ELM and LORSAL which are based on more complex machine-learning mechanism. In future, to apply the proposed framework in other urban areas and further automate the water information extraction. Taking GF-4 satellite data in residential areas in Jiashan country as experiment Wei Wu et al,[13] proposed a remote sensing identification method based on GF-4 satellite and the recognition ability of the GF-4 satellite to the residential area is analyzed. The remote sensing recognition of residential areas is mainly divided into four steps. (I)Super resolution image enhancement technology is used to improve the spatial resolution of GF-4 satellite PMS image. (II) Then, the resolution enhanced image is processed by geometric correction, radiometric calibration and atmospheric correction. (III) The existing land use and land cover data selected as prior knowledge to select typical sample areas. Based on the spectral characaterisitics and spectral relationships of different objects in GF-4 satellite image, decision-tree classification method is used to estimate the obvious non-residential areas such as cloud, vegetation, water and shadow so as to reduce the subsequent data processing and reduce the false recognition rate in residential areas. (IV) Finally, SVM classifier is selected for the classification of residential areas. The spatial scope of the country and township residents can be effectively identified in GF-4 enhanced image. The experimental results show that the resolution of GF-4 satellite image is enhanced to degree after super resolution image enhancement. The user accuracy and producer's accuracy of resident recognition by this method are 89.96% and 91.94% kappa for residential and non-residential areas is 88.12%. For GF-4 satellite image without resolution enhancement, the same residential land recognition method is used and the user accuracy and the producer accuracy are 71.8% and 89.74% respectively. Here, it is still difficult to identify the area of the village. Benqin Song et al,[14] proposed the approach combines the advantages of sparse representation classifier and kernel functions to appropriately represent target samples and provide good classification results. The proposed algorithm were evaluated using three multispectral/hyperspectral data sets. Here SVM classifier is used to estimate the probability that a positive training sample has been labeled which is required by PUL classifier. In the proposed OCC-SR and OCC-KSR methods is the acceptance rate λ which is similar to the recognition fraction parameter in other occ methods and used to obtain the reconstruction residual threshold. Although λ is determined by trial and error in this study, it is also found from the experimental results that the optimal threshold values of λ mainly ranged from 0.7 to 0.9 in all three study areas. In addition, the RBF kernel width parameter γ also needs to the set in the proposed OCC-KSR. However, an optimal value of γ could also be obtained by cross-validation i.e. when the fraction of target samples that are rejected reach a given value. This method provides two advantages. First, in the considered OCC methods, there is an explicit training stage and training data are only used in the training stage. Second, to improve data separability between the target class and the outlier class, the training samples from the target class are method into a high-dimensional features space using a kernel function to build the learning dictionary. The OCC is then conducted in the new feature space.We note that PA is closer to UA in the OCC-KSR results then in other methods in the experiment 10% igher than PA in OCC-KSR for the JM class, which the difference in accuracy between PA and UA are atleast 40% for other methods. The OCC-KSR approach achieves a relatively higher acceptable PA and UA which leads to a better classification performance in OCC. The map provided by OCC-KSR is more homogeneous and exhibits a lower number of false positives. Yaakoub Boualles et al,[15] addressed the semantic gap problem in high-spatial resolution remote sensing images retrieval.They proposed a useful semantic image representation that improves the understanding of the machine with respect to the human perception. They implemented remote sensing scene classification convolutional neural network (CNN) model to detect the semantic concepts. The similarity distance is calculated to retrieve the most similar images to the given query image. Then, to improve the performance of the retrieval results, a relevance feedback phase has been proposed, which ensures that the final result corresponds to the user need. This method shows promising results and improve the retrieval quality with respect to state-of-the-art approaches. This semantic retrieval scheme includes image decomposition, image representation, similarity matching and relevance feedback. Image are decomposed by under the principle of Quin-tree decomposition. Each block represents a scene class.A remote scene classification deep learning model is used to classify the obtained image blocks. Then the semantic image feature is generated based on the extracted semantic concepts. Here, the pre-trained low dimensional convolutional neural network(LDCNN) to classify the image blocks. The LDCNN architecture consists of the linear convultional layer, a multi-layer perception convolutional layer, a global average pooling layer followed by soft-max classifier. The images are collected from Google Earth imagery or via the Google map API for US cities with a high spatial resolution. To test the framework in terms of query response time, they compare it with two active learning RF techniques: SVM active learning which is used to classify the images based on the user selection. This method achieves a high average precision in just three RF iterations which improves the query-response time of the compared methods due to small number of Rochio's Formula iterations provided by the user. Wenzhi Liao et al, [16] a local graph-based fusion(LGF) method proposed to couple dimension reduction and feature fusion of the spectral information(i.e. the spectra in the HS image) and spatial information(extracted by morphological profiles).In the proposed method, the fusion graph is built on the full data by moving a sliding window from the first pixel to the last one. This yields a clear improvement over a previous approach with fusion graph built on randomly selected samples. Compared to the methods using only single feature and stacking all the features together, the proposed LGF method improves the overall classification accuracy on one of the datasets for more than 20% and 5% respectively. Experiments were run on two datasets such as northwestern Indiana captured by Airborne Visible /Infrared Imaging Spectrometer(AVIRIS) and urban areas in the city of Pavia, Italy captured by reflective optics system imaging spectrometer (ROSIS). The proposed LGF probes an image with an sliding window, calculate the KNN and the current pixel considering the neighboring samples included by the window and build the fusion graph within this sliding window. Here SVM classifier used, as it performs well with a limited number of training samples, limiting the Huges phenomenon. The SVM classifier with radial basis function-RBF kernels is applied. It reduce the computational complexity of calculating pair wise distance matrix to $O(BNS^2)(S<<N)$, as well as a significant reduction in memory use. Recently, some approaches show great improvements in the classification of remote sensing images by using APs and by combining post processing, which will be exploited in our future work. Md. Ali Hossain et al, [17] a one-class oriented approach for effective feature selection and classification of remote sensing image is proposed. Two data sets were used in the experiments one is an AVIRIS hyperspectral data and the other consists of a combination of AISA hyperspectral data and LiDAR data.For each data set, experiments were conducted for two cases: In first case, one of the input classes was treated as a target and remaining classes were considered as background and the classification was conducted using the features which can maximize the separation of the target class from the background. The same process was repeated for every class. In the second case, a single-stage classification was conducted using the selected set of features based on the requirements of all the classes of interest. Cluster –

space classification and Kernel SVM techniques were used for the classification for each test case. For instance, in CSC the labeled samples of ground, vineyard, roads are 90.18%, 85%, 99.12% respectively whereas for the all-class case, 85.86%, 58.04%, 94.13% respectively. With the kernel SVM the accuracy of soybean-notill, woos, soybean- min are 86.11%, 97.93%, 94.50% respectively. For AVIRIS data which is significantly higher than in all-class cases. Mutual Information (MI) is used as the feature selection criterion to cope with a wide range of data types. Then a cluster space (cs) representation is applied to model multimodel data and classifies each target class in turn. Hyperspectral and LiDAR data sets were used in the experiments. The test results demonstrate the advantage in terms of classification accuracies by focusing on one class at a time as compared to considering all classes simultaneously in classification. The advantage of this MI and CS representation is the enhanced capacity in data relevancy analysis from multiple sensors and heterogeneous data modeling. MI is utilized for feature selection because it has the ability to handle non-linear relationship between the variables and not limited to numerical data only. The CS representation can model multimodel data using multiple clusters.It can also determine the required number of features and clusters to use through evaluating the class separability. Here, that the wtraining data are available for each class but in practice such data may be available only for the target classes. When there are no labeled samples for background, classification with the methods presented here becomes harder, which will be the issue that we will address in our future research. Future work will also include the wider tests on various alternatives and options, including an interesting alternative of SVM which may provide strong performance on the weakly labeled data. Victor-Emil Neago et al, [18] extended the existing SVM by a novel approach for semi-supervised classification of remote sensing imaging using {K-means + (GMM-EM)} clustering cascade followed by selection of an amount of clustered pixels to be added to the training set according to their GMM responsibilities. This method has the following steps: (a) clustering of the multispectral pixels using the cascade composed by K-means followed by the Gaussian Mixture Model(GMM) with expectation maximization(EM) (b) selection for addition to the training set of an amount of clustered pixels according to their GMM responsibilities using one of several chosen rules (c) train semi-supervised SVM (S3VM) using both the selected clustered pixels and also the few authentically labeled ones; (d) S3VM classification.The performance of the proposed algorithm are evaluated using a LANDSAT 7 ETM+ image in the city of Kosice located in eastern Slovakia and its environs. According to the experimental results, the S3VM has led to a significant improvement in performance over the supervised SVM. The maximum recognition score increases with 12.26% from 79.44% for SVM to 91.70% for S3VM. D. Kulkarni, [19] random forest package of the Comprehensive R Archive Network-CRAN and ERDAS imagine software to implement the classifiers. Two Landsat scenes was used as input data. In order to train each classifier we selected 4 classes: water, vegetation, soil and forest. Two training sets for each class consisting of 100 points each, were selected interactively by displaying the raw image on the computer screen and selecting a 10*10 homogeneous area. The classifier were trained using the training samples and reflectance data for bands 1 through 7. Confusion matrix was adapted to assess the accuracy of the classifiers. This work has proved that the performance of random forest was better than all other classifiers in terms of overall accuracy and kappa coefficient. Juan Deng et al, [20] developed a new algorithm combined random forest classifier and multi-features is proposed in this paper. The basic idea of proposed approach is: first, K-means clustering method is used to get the clustering center of the input features and then a certain number of labels ground the center of the cluster sample are selected. Second, random forest model is chosen for image classification. In order to verify the effectiveness of proposed method, several real data experiments have been done. The experimental results show that, compared to Function of mask (Fmask), the proposed approach has higher accuracy. This method used to solve the feature selection and the threshold value setting problems. The real data experiments demonstrate that the proposal approach can determine cloud detection model and threshold adaptively. Comparing to Fmask algorithm, the proposed approach can gets higher detection accuracy. So, it is a new effective algorithm for the cloud detection of remote sensing images. Color descriptor and spectra descriptor are adopted to describe the cloud pixels character and the difference between tht cloud pixel and non-cloud pixel. Then, the multi-features are put into the K-means algorithm to get the training data. Finally, randaom forest was trained and the cloud and cloud shadow can be detected form the remote sensing images. The new model for cloud-detection is automatic, fast, accurate and robust. For the experimentsw, they selected three Landsat ETM+ images distributed in three different earth surfaces underneath including green vegetables, dessert and bare rock. Numerical results show that cloud general accuracy of cloud is 95% being more 17.7% than Fmask(77.3%). For cloud shadow detection, the proper approach can also get significantly higher accuracy than Fmask algorithm. There are some improvements in this method in the future. First, much more common features for the remote sensing data should be exacted in order to make the model applicable to different. Then, we should combined including texture, intensity and color distributions, rather than a single spectra feature. Huanxue zhang et al, [21] used random forest classifier for crop classification using multispectral RapidEye Imagery over two study sites, one in Hongxing Farm in China and other in Casselman in Cananada. Both Vegetation Indices(VIS) and textual features were derived from the RapidEye Imagery and used for classification. A total of eight types of textural features were derived using four different window sizes from both the RE and the near-infrared bands. To reduce redundancies among the VIS and textural features, feature selection using the principal discriminant analysis was performed. Results, showed that the overall classification accuracy was improved by ~7% when the RE inidices were combined with the five spectral bands in classification as compared with that using the five bands alone. Furthermore, when all the features such as band reflectance, VIS and texture were used, the overall classification accuracy increased. Four steps of standard image preprocessing were conducted on the Rapid Eye images, including: Radiometric calibration to convert the raw digital number to radiance, Atmospheric correction using FLAASH module, Geometric correction using a polynomial model with GCPs with the nearest-neighbor resampling method, Subsetting the images to the study site. Feature extraction is the classification process is to define feature in the remotely sensed imagery to characterize different crops. Spectral and textural features are two fundamental types of features commonly used in image interpretation and classification. Feature selection is necessary to identify the most important features to be included in the classification. Here, PCA, Correlation Analysis(CA) and the stepwise discriminant analysis(SDA) were adopted for feature selection. Random Foreset classifier is an ensemble classifier that uses a set of classification and regression trees to make a prediction. RF used here consists of using randomly selected features or a combination of features at each node to grow a tree. Bagging, a method to generate a training dataset by randomly drawing with replacement N pixels, Where N is the size of original training set, was used for each feature/feature combination selected. This makes the RF classifier more robust against data noise and overtraining than other classifiers based on bagging or boosting. Here the overall accuracy of Hongxing farm site is 82.36% and Casselman is 83.67%. Min-Tan Pham et al,[22] demonstrated local feature based attribute profile (LFAP) have to improve the classification performance of very high resolution(VHR) remote sensing images. For better dealing with spatial and texture information, statistical features of local patch are extracted to replace each AP's filtered pixel. Here, two simple first-order features including the mean and range have been exploited and proved to the relevant for characterizing smooth textures from AP filtered images. It proved superior performance of LFAPs compared to standard APs and the histogram-based approach. In order to evaluate the effectiveness of the approach, supervised classification using random forest classifier is performed on the VHR panchromatic Reykjavik image. This technique has improved more than 6% of OA from the standard APs. The construction of LFAP is not limited to the use of mean and range features. Any other local features can be extracted to tackle more complex VHR image scenes in future work. Also, the concept of LFAPs can be applied to the extended APs for hyperspectral image classification as well as to the recently proposed self-dual APs which has been proved to outperform APs. Pedram Ghamisi et al, [23] generated the novel method for the analysis of remote sensing data based on Extinction Filers carried out on two well-known high-resolution panchromatic data sets captured over Rome, Italy and Reykjavik, Iceland. Here Extinction Profile composed of a sequence of thinning and thickening transformations applied to a grayscale image.This method adopted a few new attributes, such as volume and height for the first time in the remote sensing community. The obtained results compared with one of the strongest approaches in the literature, Attribute Profile-AP from different points of view, including classification accuracies, the complexity analysis, and the simplification and recognition rate. The method works with the number of extrema which provided better results in terms of classification accuracies and decreases the burden of setting threshold values, which was shortcoming for conventional APs. It leads to future work to investigate the use of EP for other types of remote sensing data and evaluate the efficiency of different classifiers for the classification of features produced by EP. Here for the classification step, random forest classifier taken into account since it can efficiently handle the high redundancy existing in features produced by EPs. Wen Zhou et al, [24]proposed a scene division based stratified object-oriented image analysis method. Since image's hue information can quantity color information and make the similar color have similar hue values. So, image hue information has become the mainly basis of scene division and in order to use this information effectively, second order matrix was used to reflect the relationship of hue values. Second order matrix can reflect image's visual complexity, so it can be used to divide the overall image into simple and complex objects occupied scenes. The complex objects occupied scenes can be re-divided into several scenes of which the composition is simple or single. In order to set segmentation parameters accurately and quickly, spatial estimation method was used to calculate every scene image's scale parameter, thus optimal scale can be selected for every scene. Since the complexity of data is effectively reduced by dividing the overall image into several scenes, and spatial estimation method can help select optimal segmentation parameters, so the final classification result can be improved efficiently, and the experiment result also proved the effectiveness of the proposed method. QuikBird Pansharpened image of Hualien city, Taiwan, china was selected as experimental image. Multiscale segmentation method is used for segmenting. The result shows that the value of estimated scale parameter(hr) is very closed to the optimal scale parameter value. That proved the effectiveness of using SV to estimate multiscale segmentation method's scale parameter. Merged image's accuracy and KIA based on Scene image's estimated scale parameter is better than overall image's optimal result, and compared to overall image's optimal result, both the accuracy and KIA has improved 9.6% and 7.2% when using estimated hr parameter to segment scene image and the merging scene image's classification result.The stratified object oriented remote sensing image classification method has a great significant to object extraction and classification from high resolution remote sensing images. Further improvements on this research will focus on how automatically calculate the value of hs and hr. Xiang-bing et al, [25] The common classification methods regards every pixel as the basic unit for medium-resoultion and multispectral remote sensing image. However due to the limited spatial resolution and the complexity of surface features distribution, there are a lot of mixed pixels in medium-resolution and multispectral remote sensing image, which has seriously hampered the effectiveness and accuracy of this common classification methods. Here, medium-resolution and multi-spectral remote sensing image classification taking the study of Chabagou watershed in Loess plateau as the study area and the Landsat8 OSI image for the study data. First, the end members are selected based on the pretreated remote sensing images, including radiometric calibration, atomospheric correction and image fusion. Then the abudance of various end members is got through fully constrained linear mixed pixel decomposition model, and also the sub-pixel level distribution for all kinds of surface features. Classification rules are constructed according to the distribution of various types of surface feature and auxiliary data of the study area such as the slope and aspect generated from DEM. Experimental results show that this method has higher classification accuracy. However, this method required more parameter settings. So in future, it is necessary to reduce the number of parameter settings to improve the processing time.

III. CONCLUSION

This paper presents a survey on recent developments from classification techniques in remote sensing data and its application. So far we have reviewed object-oriented classification, ELM, Maximum Likelihood classification (MLC), 1NN –DTW pixel classification; random forest classifier, SVM and we believe the exploitation and adaptation of classification techniques in remote sensing imagery still remains an open research topic for on-going as well as future work.

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