Photonirvachak

Springer

. Indian Soc. Remote Sens. (June 2010) 38 : 203-210

RESEARCH ARTICLE

Some Issues Related with Sub-pixel Classification using HYSI Data from IMS-1 Satellite

A. Kumar • A. Saha • V. K. Dadhwal

Received: 15 October 2009 / Accepted: 3 February 2010

Keywords Sub-pixel • Support vector machine • Sub-pixel confusion-uncertainty matrix (SCM) • Uncertainty.

Abstract The mixed pixels are treated as noise or uncertainty in class allocation of a pixel and conventional hard classification algorithms may thus produce inaccurate classification outputs. Thus application of sub-pixel or soft classification methods have been adopted for classification of images acquired in complex and uncertain environment. The main objective of this research work has been to study the effect of feature dimensionality using statistical learning classifier - support vector machine (SVM with sigmoid kernel) while using different single and composite operators in fuzzy-based error matrixes generation. In this work mixed pixels have been used at allocation and testing stages and sub-pixel classification outputs have been evaluated using fuzzy-based error matrixes applying single and composite operators for generating matrix. As sub-pixel accuracy assessment were not available in commercial software, so in-house SMIC (Sub-pixel Multispectral Image Classifier) package has been used. Data used for this research work was from HySI sensor at 506 m spatial resolution from Indian Mini Satellite-1 (IMS-1) satellite launched on April 28, 2008 by Indian Space Research Organisation using Polar Satellite Launch Vehicle (PSLV) C9, acquired on 18th May 2008 for classification output and IRS-P6, AWIFS data for testing at sub-pixel reference data. The finding of this research illustrate that the uncertainty estimation at accuracy assessment stage can be carried while using single and composite operators and overall maximum accuracy was achieved while using 40 (13 to 52 bands) band data of HySI (IMS-1).

A. Kumar[1] (✉) • A. Saha[2] • V. K. Dadhwal[1]

[1]Indian Institute of Remote Sensing, Dehradun-248001, India

[2]Vellore Institute of Technology, Vellore, 632014, India

email: anil@iirs.gov.in

J. Indian Soc. Remote Sens. (June 2010) 38 : 203-210

Introduction

The most widely used method for extracting information from remotely sensed data is image classification. Research into the problem of land cover classification using multispectral remotely sensed data has been ongoing since the early 1970s, when ERTS (later Landsat-1) multi-spectral scanner (MSS) data became available. Classification techniques such as the parallelopiped, minimum distance to mean and maximum likelihood methods were developed. Perhaps surprisingly, the accuracy of land cover classification was not necessarily improved (and, in some cases, was reduced) by the use of higher spatial resolution data and by the availability of additional bands in the near and mid-infrared wavebands (Cushnie, 1987). Woodcock and Strahler (1987) suggested that this phenomenon is the consequence of an increase in within class spectral variability as spatial resolution increases (i.e. pixel size decreases). Hughes (1968), have reported that classification accuracy decreased, as additional features were included. This effect has been termed “the curse of dimensionality”.

In 1990s onwards hyperspectral data was available to remote sensing application users. So, till 1990s the available classification techniques were not sufficiently powerful to identify patterns in hyperspectral data. In this study statistical learning based classifier; Support Vector Machine (SVM) has been evaluated. There are two main types of classification method, namely supervised and unsupervised approach. Both methods may be applied to perform hard and sub-pixel classification. In hard classification, pixel is allocated to one and only one class, which may produce erroneous results, particularly in classifying coarse spatial resolution images. It is important that sub-pixel classification is used to produce class proportions within a pixel in order to increase the classification accuracy and to produce meaningful and appropriate land cover composition. The main objective of this research work was to study the performance of SVM-based classifier while applying sub-pixel approach at allocation as well as at testing stage. So the objectives of this research work are stated as follows:

- To study the effect of number of features on sub-pixel classification accuracy.
- To assess sub-pixel classification output with different testing algorithms.
- To assess the uncertainty of the confusion, that reflects the uncertain nature of class sub-pixel distribution.

While achieving objectives of this research work the reference data as fraction images have been generated from IRS-P6, AWIFS sensor at 60 m spatial resolution, which is approximately multiple of 10 with HySI data, acquired on same data.

Literature review

Few published research work have been found related to these research work, which have been mentioned in this section as follows:

Mahesh and Mather (2003) have studied MLC, ANN, DT and SVM classifiers for land cover classification. They have studied for two project areas; the first area used in the report is near town of Littleport in eastern England. The second is a wetland area of La Mancha region of Spain. For the Littleport area, ETM^+ data acquired on 19th June 2000 was used. The classification problem involves the identification of seven land cover types (wheat, potato, sugar beet, onion, peas, lettuce and beans) from the ETM^+ data set. For the La Mancha study area, hyperspectral data acquired on 29th June 2000 by the DAIS 7915 airborne imaging spectrometer were available. Eight different land cover types (wheat, water body, dry salt lake, hydrophytic vegetation, vineyards, bare soil, pasture lands and build-up area) were specified. Random sampling was used to collect the training and testing samples for both data sets. Total selected pixels were divided into two part, one for training and one for testing the classifiers, so as to remove any possible bias resulting from the use of same set of pixels for both testing and training phases. A standard back propagation neural network classifier was used. All user-defined parameters are set as recommended by Kavzoglu and Mather (2003). Like ANN classifier the performance of SVM depends on a number of user-defined parameters, which may influence the final classification accuracy. For the study, a radial basic kernel with penalty value C=5,000 is used for both data sets. The values parameters were chosen after a number of trials and the same parameters are used with the DAIS data. Results obtained using ETM^+ data suggests that the SVM classifier perform well in comparision with ANN and MLC. Further the training time taken by SVM is 0.3 minutes in comparison of 58 minutes by the ANN on a dual processor machine. Results suggest that SVM performance is statistically significant in comparison with ANN and MLC classifiers. To study the behavior of SVM classifier with hyperspectral data a total of 65 bands are used as the combination of first 5 bands, first 10 bands, etc. giving a total of 13 experiments. Results obtained from analysis of hyperspectral data suggested that SVM classifier increase almost continuously as a function of number of features, with the size of training data set held constant, whereas the overall classification accuracies produced by the MLC, DT and ANN classifiers decline slightly once the number of bands exceeds 50 or so. They concluded that SVM outperforms MLC and ANN in terms of classification accuracy with both data sets. Several user-defined parameters affect the performance of SVM classifier, but it is easy to find appropriate values for these parameters than it is for parameters defining the ANN classifier. The level of classification accuracy achieved by SVM classifier is better than both MLC and ANN classifiers when used with small number of training data.

Aziz (2004) has evaluated the soft classifiers for multi-spectral remote sensing data, and this study has focused on two statistical classifiers; MLC and linear mixture model (LMM), two fuzzy set theory based classifiers; fuzzy c-means (FCM) and probability c-means (PCM) and two neural network classifiers; back propagation neural network (BPNN) and competitive learning neural network followed by learning vector quantizers (CLNN-LVQ). IRS 1B LISS-II data has been used for classified and IRS 1C PAN image derived reference map registered to LISS-II has been used for testing image. The hypothesis of fuzzy error matrix (FERM) has been promoted to assess the accuracy of soft classification. As the formulation of majority of these classifiers and accuracy measures in the existing commercial image processing software are not available, so Soft Classification Methods and Accuracy Assessment Package (SCMAP) has also been developed. The results showed that the distribution free classifiers based on fuzzy set and neural network produced more accurate classification than the statistical classifiers. An improvement in accuracy of 8%-12% was observed. It was shown that how PCM classifier was robust to the existence of noise in the data. CLNN-LVQ produced the highest classification accuracy of 53.89% and showed an improvement of more than 5% over the FCM. The accuracy of hard classification was further increased by including a *priori* probabilities in BPNN and MLC classifiers. A new approach to include a *priori* probabilities by way of replicating the training data of a class in accordance with the proportional area covered by that class on ground was suggested. The accuracy of BPNN classifier increased by 20% whereas the accuracy of MLC increased by 7% on the inclusion of a *priori* probabilities. Evaluation of soft classification through FERM (Binaghi *et al.*, 1999) based measures led to an improvement of the order of 20% in the accuracy of the classification over the accuracy determined from traditional error matrix based measures for the same classification. Thus, it is recommended that soft classification outputs from any classifier should not be hardened for evaluation purposes, as this may results into loss of information. LMM as soft classifier produced the lowest accuracy whereas BPNN and PCM as soft classifiers produced the highest map accuracy of about 73%, which was an improvement of 20% over the highest accuracy achieved by the unsupervised classifiers. When the images are dominated by mixed pixels, their incorporation not just in allocation stage through generation of soft outputs, but also in training and test stages were also assessed. The results showed that by properly accounting for mixed pixels in all stages, same level of accuracy could be achieved as would have been obtained by using pure pixels in all stages.

Mahesh and Mather (2006) have studied the sub-pixel classification of hyperspectral DAIS and Landsat-7 ETM$^+$ data applying four algorithms (such as, maximum likelihood, decision tree, ANN and SVM) and made the comparison of accuracy assessment, for the area of La Mancha Alta, South of Madrid, Spain. They concluded that no reduction in classification accuracy was observed as the number of bands was increased, even with the small training data set of 100 pixels per class. However, classification accuracy starts to stabilize once a threshold number of bands are reached. The SVM produce higher classification accuracies than others with small training data sets. The effect of using different sampling plans was investigated and it was found that MLS classifier produces higher classification accuracies when the training data were sampled randomly than those achieved using a systematic sampling plan. Both sampling plans produced similar results with SVM, DT and ANN. The level of classification accuracy when 13 MNF components used were lower than those obtained by classifying the raw data, indicating that the MNF technique may not be effective for dimensionality reduction in the context of classification with this type of data. The use of DT based feature selection techniques and the accuracy achieved was close to the level reached using raw data, suggesting that the DT approach can be effectively used for feature selection with hyperspectral data. The ML classifier shows a greater dependence on the characteristics of the training data than do the other methods. This result indicates that the ML method does not generalize well to unknown cases. The SVM algorithm was least affected by the nature of the training data.

The review of literature suggests that there is a range of sub-pixel classification methods proposed and implemented by different researchers. From among a number of sub-pixel classification methods, this paper has focused on statistical learning method (SVM). These published works does not reflect evaluation part of sub-pixel classified output. So, Fraction images generated from SVMs method has been evaluated using different fuzzy error matrixes generated using single (Binaghi *et al.*, 1999) and composite operators (Silván-Cárdenas and Wang, 2007). This is a new approach that has been developed to assess the accuracy of sub-pixel classifiers. In this case, the sub-pixel confusion can be uniquely determined. When no unique solution exists, the space of feasible solutions can be represented by confusion intervals. A new cross-comparision matrix that reports the confusion intervals in the form of a center value plus-minus maximum error was proposed to account for the sub-pixel distribution uncertainty. The new matrix is referred to as sub-pixel confusion-uncertainty matrix (SCM). The elements of the fuzzy error matrix represent class proportions, corresponding to sub-pixel reference data (R_{n-}) and sub-pixel classified data (C_m), to class n and m, respectively. Reference sub-pixel data have been generated from AWIFS data of same date.

Test site and data used

The test site is near Sambalpur, state Orrisa, near the state's border with Chhattisgarh. This ancient diamond trade center is renowned for textiles, folk dance and a variety of monuments. Sambalpur is 290 km north-west of Bhubaneswar.

The test site for this research work covers the surrounding of world's longest and largest dam, Hirakud dam that is built across the Mahanadi River, in Hirakud of Orissa. Hirakud dam intercepts 83,400 km^2 of the Mahanadi catchments. A substantial number of migratory birds flock here during the winter.

The geographic coordinates of center part of study area is 21°32'N and 83°45'E. Broadly in this area water, forest and fallow land area has been considered for sub-pixel identification and evaluation. The data used for this research work was from the Indian Mini Satellite (IMS)-1 having a hyperspectral sensor (HySI), despite its relatively lightweight. HySI has 506 m spatial resolution with 64 spectral bands. Another dataset IRS-P6, AWiFS acquired at same date has been used for testing the fraction images generated from HySI data.

Optimum parameters of classification algorithms and outputs

For SVMs, sigmoid kernel was studied with, the optimum penalty value *C* has been used from Varshney and Arora (2004). The optimum penalty value adopted is shown in Table 1.

For accuracy assessment of each classified images generated from SVM-based classification algorithm have been computed by using fuzzy-based error matrixes using single and composite operator in SMIC software developed at Indian Institute of Remote Sensing, Dehradun. The classified images and reference images had been taken as HySI rule images and AWISF (IRS-P6) rule images, respectively. For accuracy assessment of the rule images, 300 (100 samples per class; total three classes) samples, outside the training area, have been collected from fraction images generated from AWIFS image of IRS-P6 satellite as reference image as well as from fraction images generated from HySI image from Indian Mini Satellite (IMS)-1, dated 18 May 2008. These testing sample sizes have been equivalent to the sample size of 75-100 pixels per class as recommended by Congalton (1991) for accuracy assessment purpose.

Table 1 Optimum penalty values for different kernel types

Sl.	Kernel	Penalty value (*C*)	
No	Type	Hyperspectral	Multispectral
1	Sigmoid	7500	0.75

Results and discussion

In this research work influence of feature dimensionality on classification accuracy is assessed using the HySI, IMS-1 data. Also it has been accessed the sub-pixel classification accuracy with different methods while trying to access with kappa coefficient. It has also been tried to estimate the uncertain nature of classes sub-pixel distribution. With a fixed number of training data as the number of bands is progressively increased from 10 to 50. Five subsets of HySI (IMS-1) bands had been extracted, comprising bands, 13-22, 13-32, 13-42, 13-52 and 13-62, respectively and other bands where find as noisy data. The classification was performed using SVM with sigmoid kernel with training data set size of 20 sample pixels per class randomly. The effect of dimensionality on classification overall accuracy achieved from SVM with sigmoid kernel using fixed training data size is shown in Fig. 1. The effect of dimensionality on fuzzy kappa coefficient achieved from SVM with sigmoid kernel using fixed training data size is shown in Fig. 2, 3. shows variation in overall accuracy uncertainty with increasing number of bands for training sample sizes of 20 pixels per class, this reflect the uncertain nature of classes sub-pixel distribution. Fig. 4 shows variation in fuzzy kappa coefficient uncertainty with increasing number of bands for training sample sizes of 20 pixels per class, this reflect the uncertain nature of classes sub-pixel distribution.

a) Classification accuracy using the SVM algorithm (with sigmoid kernel) has been 69.83%, 68.8%, 61.07%, 80.17% and 57.43% when 10 bands (13-22 bands of HySI, IMS-1 data) while using FERM, SCM, MIN-PROD, MIN-MIN and MIN-LEAST were used, respectively.

b) The maximum overall accuracy with SVM algorithm (with sigmoid kernel), 82.60% occurred while applying MIN-MIN operator,

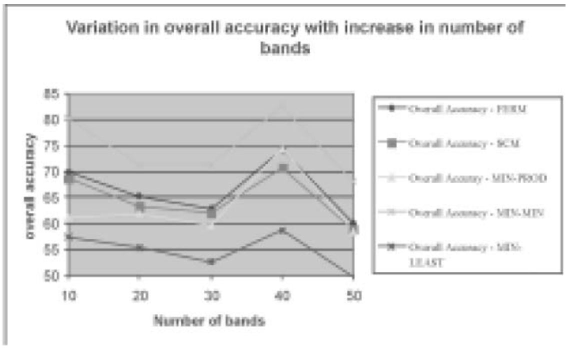

Fig. 1 Variation in overall accuracy with increasing number of bands for training sample sizes of 20 pixels per class

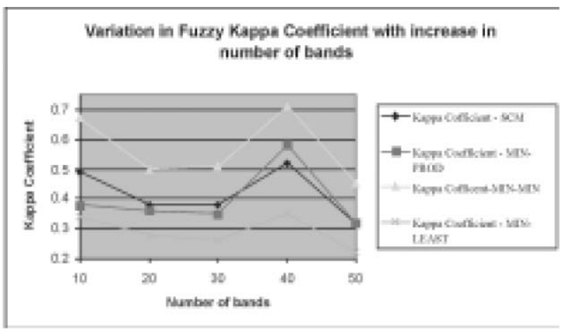

Fig. 2 Variation in fuzzy kappa coefficient with increasing number of bands for training sample sizes of 20 pixels per class

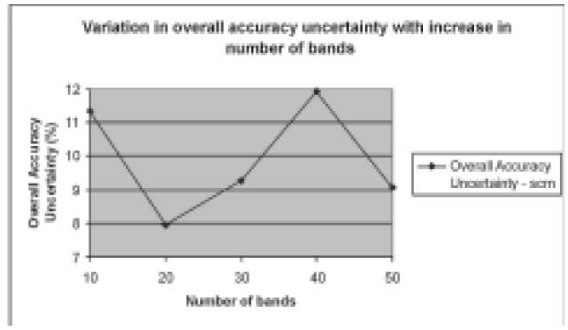

Fig. 3 Variation in overall accuracy uncertainty with increasing number of bands for training sample sizes of 20 pixels per class

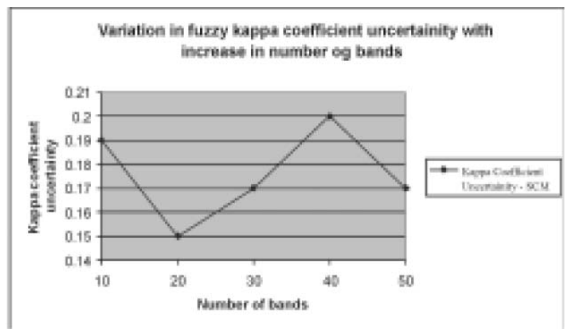

Fig. 4 Variation in fuzzy kappa coefficient with increasing number of bands for training sample sizes of 20 pixels per class

when the bands combination of 13-52 bands dataset of HySI (IMS-1) data with 20 samples per class was used.

c) The maximum overall accuracy has been achieved while using 40 bands (13-52 bands) of HySI (IMS-1) data. This maximum overall accuracy has been with different methods of fuzzy-based error matrixes using 40 bands (13-52 bands) of HySI (IMS-1) data, shown in Fig. 1.

d) The results have been evaluated while generating fuzzy kappa coefficient using single and composite operators. Fuzzy kappa coefficient also got maximum values while using 40 bands (13-52 bands) of HySI (IMS-1) data with single as well as composite operator for generating fuzzy-based matrixes shown in Fig. 2.

e) Unfortunately, the accuracy indices so derived cannot reflect the uncertainty of confusion, as they do not depend on the off-diagonal cells. As the U-values (internal half width) reflect the sub-pixel distribution uncertainty, which is not considered for the agreement, these are zeros for the diagonal cells. To estimate the uncertainty U-values of overall accuracy and kappa coefficient have been used in SCM with different bands data sets of HySI (IMS-1), shown in Fig. 3, 4 respectively.

Conclusion

The objective of this research work was to understand the behaviour of SVM with sigmoid classification algorithm with variation in dimensionality of feature space. In this research work, five data sets of different feature space with a multiple of 10 were prepared from HySI (IMS-1) data of 64 bands. The reference data set in the form of fraction images was prepared using IRS-P6, AWIFS sensor. While accuracy assessment of classified data has been done with fuzzy-based error matrix approach using single and composite operators. The conclusions of this research work are as follows:

a) While using data set of different bands from HySI sensor, maximum overall accuracy, 82.6% with MIM-MIM operator was achieved while using 40 bands (13 to 52 bands of HySI).

b) In this research work it has been tried to assess the fraction images with fuzzy-based error matrix with single and composite operators. The single operator used was MIN and composite operators used were MIN-PROD, MIN-MIN, MIN-LEAST and SCM. The maximum overall accuracy was obtained from MIM-MIN operator while using different bands data set of HySI.

c) It was possible to assess the uncertainty of the confusion that reflects the uncertain nature of class sub-pixel distribution in overall accuracy as well as in kappa coefficient as shown in figure 3 and 4. The trend for uncertainty in overall accuracy and kappa coefficient was same as overall accuracy as well as in kappa coefficient from different operators.

Future scope

Hyperspectral remote sensing holds the potential to provide a high spectral data obtained about the earth surface features. By using coarser resolution hyperspectral data, a sub-pixel classification method can give the proper high classification accuracy and more accurate results to identify the minor features, (within classes). Classification accuracy depends on a number of factors, of which the nature of training samples, the number of bands used, the number of classes to be identified relative to the spatial resolution of the image and the properties of the classification algorithms are the most important. This research evaluates the effect of these factors on classification accuracy using test data of HySI (IMS-1) and IRS P6, AWIFS data as reference data. There is no evidence to support the view that classification accuracy inevitably declines as the data dimensionality and the number of training samples increase.

Classification accuracy also depends on the optimum parameters of the classification algorithms; different types of data and different algorithms have different parameters. So the learning of these optimum parameters should be carried out to train the algorithms and hence by using these optimum parameters, the exact accurate results can be calculated. The acquisition date of allocation and test images should be the same to have reference information of same time without changes but with higher spatial information. Finally, this work produces how to evaluate sub-pixel information with finer spatial resolution data set and gives a comparative study of single and composite operators for generation of fuzzy-based error matrixes.

Acknowledgement Authors are thankful Space Application Center (SAC) Ahemedabad for providing IMS-1 (HySI) test data.

References

Aziz MA (2004) Evaluation of soft classifiers for remote sensing data, unpublished Ph. D thesis, Indian Institute of Technology Roorkee, Roorkee, India

Binaghi E, Brivio PA, Chessi P and Rampini A (1999) A fuzzy Set based Accuracy Assessment of Soft Classification. *Pattern Recognition Letters* 20: 935-948

Congalton RG (1991) A review of assessing the accuracy of classification of remotely sensed data. *Remote Sensing of Environment*, 37: 35-47 [doi:10.1016/0034-4257(91)90048-B]

Cushnie J L (1987) The interactive effect of spatial resolution and degree of internal variability with land cover types on classification accuracies. *International Journal of Remote Sensing* 8(1): 15-29

Hughes GF (1968) On the Mean Accuracy of Statistical Pattern Recognizers. *IEEE Transactions on Information Theory* 14: 55-63

Kavzoglu T and Mather PM (2003) The use of backpropagating artificial neural networks in land cover classification. *International Journal of Remote Sensing* 24(23): 4907-4939

Mahesh P and Mather MP (2003) Support vector classification for land cover classification, Processing's of Map India 2003, 28-31 January, Image processing and Interpretation theme

Mahesh P and Mather MP (2006) Some issues in the classification of DAIS hyperspectral data, *International Journal of Remote Sensing* 27 (14): 2895-2916

Silván-Cárdenas JL and Wang L (2007) Sub-pixel confusion–uncertainty matrix for assessing soft classifications *Remote Sensing of Environment* 112: 1081–1095 [doi: 10.1016/j.rse.2007.07.017].

Varshney PK and Arora MK (2004) Advance Image Processing Techniques for Remotely Sensed Hyperspectral Data, Springer-Verlag, Berlin

Woodcock CE and Strahler AH (1987) The factor of scale in remote sensing. *Remote Sensing of Environment* 21: 311-332