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A COMPARISON OF VARIOUS EMERGING TECHNIQUES FOR DIGITAL CLASSIFICATION OF URBAN ENVIRONMENT

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Abstract
A comparison of various emerging digital classification approaches for classification of urban environment has been carried out in this study. It has been done on two study sites in the state of U.P. in India. These sites represent good examples of rapidly changing urban environment in developing countries. The following alternative approaches were used for the digital classification: Back propagation Artificial Neural Network (BPANN), Classification with wavelet derived texture features and the Per-field classification approach. The satellite data from LISS-III sensors on board IRS-1C satellite was used for the study. Results from these approaches were compared with the conventional Gaussian Maximum classification (GML) classification approach. It was observed that the classifications results using BPANN approach were similar to or slightly better than GML classification. Resilient propagation (RPROP) method of BPANN was the best and robust method in comparison to other BPANN methods considered for the study. Investigations were also carried out to explore significance of spatial properties in the form of texture features. These features were derived using various techniques including wavelet-based approach. Results showed that classification accuracies using texture features show significant improvement over pure spectral classification. A novel global threshold based region growing segmentation method the 'Per-field classification' was also implemented for urban classification. This approach also showed significant improvement over the per-pixel GML classification approach.

Introduction

The past five decades have seen a phenomenal increase in the growth of urban population in developing countries. All this rapid and haphazard growth of urban sprawl and increasing population pressure is resulting in deterioration of infrastructure facilities, loss of productive agricultural lands and green open spaces besides causing air pollution, health hazards and micro-climatic changes. To address these issues effectively, one requires up-to-date and accurate data at regular intervals of time on the changing urban sprawl, urban land use, urban resources and urban environment. It is here that satellite remote sensing with its ability to provide reliable and accurate data may offers excellent possibilities to map, monitor and measure the various facets of urban development. The maps prepared using conventional techniques often become obsolete even before they are published where large areas are concerned. Many researchers have advocated use of digital processing of satellite based remote sensing data for this purpose due to many advantages of these over conventional field-based and photogrammetric surveys. Satellite remote sensing, with repetitive and synoptic viewing capabilities as well as multi-spectral capabilities offer unique opportunities for mapping and monitoring some of the elements of urban core, its dynamics and the resultant urban structure. Conventionally, land use maps derived using remote sensing data have been prepared using coarse resolution satellite data with minimum distance and Gaussian maximum likelihood (GML) classification method. However, the levels of details that could be delineated were very limited. With the availability of high-resolution sensor data from satellite-based platforms, the user community hoped to achieve better results in a reliable and rapid manner. For that purpose, conventional techniques of classification were used with high-resolution satellite images of urban areas. However, the results were not encouraging.

Land use classes in urban environment are highly deviating from normal distribution and affect results from GML classification. In recent years, the non parametric classifier like artificial neural network has been developed and applied to general pattern recognition problem to deal with data deviating from normal distribution. The Land use classes in the urban environment are also spectrally mixed and spatially complex therefore inclusion of spatial information could also improve the classification accuracy. This spatial information can be included either using window-based approach or by classifying the image on per field basis (segment-based). In the above context this study presents results and comparison of a BPANN, texture and per field segmentation-based classification approach as applied to an urban environment.

Study sites and data resources

The study has been carried for two cities (Kanpur and Lucknow) in the state of U.P in India. From the study of available maps, field visits and previous knowledge about the study sites, it was observed that 15 and 12 classes covered the majority of urban land use features respectively for two cities.

The satellite data products used for the study was procured from linear imaging self scanning LISS-III sensors on board IRS-1C satellite. An extract of 512x512 pixels covering major portion of urban areas was extracted from the satellite image for the study. In addition to these satellite data products, corresponding topographic and land use maps were also used.

Literature review

The use of artificial neural networks for remote sensing data interpretation has been motivated by the realization that the human brain is very efficient at processing vast quantities of data from a variety of different sources. Neurons in the human brain receive inputs from other neurons and produce an output, which is then passed to other neurons. For some time it has been recognized that a mathematical approach based on the actions of the biological neurons may be implemented to process and interpret many different types of digital data. While it is not possible or desirable to reproduce the complexity of the human brain on a computer, artificial neural networks that are based on an architecture of simple processing elements like neurons are proving successful for a wide range of applications, including processing and interpreting remotely sensed data. The application of neural approaches in remote sensing is advocated mainly due the reasons that they perform more accurately in comparison to the other techniques such as statistical classifiers. They perform more rapidly in comparison to other techniques such as statistical classifiers; they incorporate a priori knowledge and realistic physical constraint into the analysis; it is easy to incorporate different types of data (including those from different sensors) into the analysis, thus facilitating synergistic studies; they can produce considerably better results for small training datasets compared to conventional statistical classifiers (Atkinson and Tatnall, 1997).

For spatially complex and spectrally mixed classes, the classification accuracy could improve if the spatial properties of the classes were incorporated into the classification criterion (Lee and Philpot, 1991). Textures provide important characteristics for the spatial analysis of many types of images including remotely sensed images. Considerable research has been carried out for textural analysis for the last three decades. But most of the researchers primarily focused their attention in the spatial domain. They used the first order statistics (gray level difference histogram (GLDH)), second order statistics (gray level co-occurrence matrix (GLCM)) and spatial gray level dependency matrix (SGLDM)) for the extraction of textural features (Haralick *et al.*, 1973). In the past, one difficulty of texture analysis was the lack of adequate tools to characterize textures at different scales and resolutions effectively. Recently, methods based on multiresolution analysis (MRA) have received a lot of attention (Mallat, 1989). These methods often outperform traditional second order statistics or the GMRF model. Recent developments in spatial/frequency analysis such as Gabor transform, Wigner distribution and wavelet transform (Yang and Chen, 1994) have provided good multiresolution analytical tools. Specifically, wavelet transform plays an important role in texture analysis and classification. Although some work has been done in wavelet texture analysis in the image classification and segmentation, only a few studies have concentrated towards remote sensing images.

Image segmentation has been the subject of extensive research in the areas of computer vision and pictorial pattern recognition in the recent past. The objective of using segmentation algorithm in classification of urban environment is to cater for widely different textured images of urban environments. Natural scenes often contain feature gradients, highlights, shadows, texture and small objects with fine geometric structure, all of which make the process of producing useful segmentation difficult. There are two types of image segmentation that are based on detection of boundary or growth of region. A region-based approach has been preferred because finding precise edges in such images is extremely difficult. This study presents investigation pertaining to the region-based approach of classification for a typical urban environment.

Methodology

Initial experimentations with non-parametric classifier were performed with number of variants of BPANN like standard backpropagation method, conjugate gradient algorithm, scaled conjugate gradient, BPVLR and RPROP classification. RPROP (Reidmiller and Braun, 1993) was found out to be the best and robust method, therefore, only *RPROP* method was used for further analysis. The entire methodology for experiments was divided into two phases. The first phase was related to finding out relative importance of various factors using conjoint analysis (Hair *et al*., 1998). In the second phase, subsequent experiments were performed with selected factors decided upon after conjoint analysis.

The methodology for window-based texture classification was also divided into two phases. In the first phase, factors considered for GLCM texture analysis was assessed using conjoint analysis. In the second phase, GML classification was carried out with selected factors and classifications were also carried out with wavelet-derived texture feature using selected factors.

The investigations with segment-based approach used three different thresholding methods, namely Johannsen and Bille (1982), Otsu (1979) and Trussel (1979). After getting threshold values of multispectral bands, mulstispectral image segmentation was done. This image was further refined by a region-merging approach proposed by Beveridge *et al.* (1989). Finally, for classification of segmented image into land use classes, the per-pixel and the per-segment GML classification approaches were used.

The overall classification accuracy and the accuracy of the individual classes were assessed by computing *Khat* indices and associated asymptotic variances. Pairwise statistical tests were performed to assess the significance of any differences observed between two classifications using a *Z* statistics (Congalton and Green, 1999).

Results and Conclusions

The per-pixel GML spectral classification for urban land use classification has limited success due to high intra class variation and similarity of biophysical environment resulting in poor separation. Moreover, most of the classes have been observed to follow non-normal behaviour. Out of various factors such as sample size, hidden layers and number of epochs considered in RPROP classification studies, sample size has the highest relative importance affecting classification accuracy followed by the first hidden layer and the number of epochs. With the increase in sample size, the accuracy increases. Relative importance of second hidden layer is very low indicating its least effect on accuracy. This suggests that only one hidden layer is sufficient for *RPROP* classification. Higher classification accuracy was achieved using RPROP in comparison to GML classification, although this increase in accuracy was statistically not significant.

It was observed from the results that grey level co-occurrence matrix (GLCM) texture features improved classification results in a significant manner. With the increase in window size, the accuracy increased but for every texture feature there was an optimum window after which this increase was statistically not significant. Inclusion of texture feature *Mean* has the highest effect on classification results followed by *Contrast*. Out of the four factors investigated to find out their relative importance in GLCM texture classification, choice of texture feature has highest relative importance followed by size of window used for extracting texture feature. Factors, like quantization level of image and choice of image band for extracting texture features have lesser relative importance respectively indicating their lesser influence on classification accuracy. Inclusion of wavelet derived texture feature in the classification process improved classification results in a significant manner. For the wavelet derived texture classification, choice of texture feature was observed as the most important factor affecting classification accuracy followed by choice of window size and decomposition level. These finding were similar to GLCM derived texture classification. A combination of approximate and 3 detail images is preferable over only approximate image for extracting texture features. Decomposition of images up to the first level is sufficient and there is no need to go for further decomposition. Table 1 shows classification results for Lucknow study site with spectral and spectral + wavelet-derived texture features at optimum window sizes using GML classification.

Table 1. Accuracy with spectral and spectral + wavelet-derived texture features at optimum window sizes using GML classification

S. no.	*Class name*	*Test accuracy*						
		Features				*Z-statistic*		
		a	*b*	*c*	*d*	z_{ba}	z_{ca}	z_{da}
1	Agriculture-1	0.78	0.93	0.94	0.94	2.71	3.01	3.01
2	Agriculture-2	0.77	0.87	0.90	0.95	1.62	2.35	3.50
3	Commercial	0.71	0.82	0.93	0.98	1.68	3.79	5.08
4	Educational institutes	0.53	0.57	0.66	0.78	0.44	1.71	3.42
5	Government establishment	0.11	0.51	0.51	0.50	6.07	6.05	5.93
6	Grassy land	0.89	0.86	0.92	0.88	-0.70	0.53	-0.25
7	High residential	0.81	0.88	0.87	0.90	1.30	1.08	1.81
8	Medium residential	0.85	0.93	0.94	0.90	1.55	1.85	1.01
9	Park	0.73	0.80	0.88	0.83	1.12	2.41	1.57
10	Reserve forest	0.90	0.89	0.94	0.99	-0.20	0.91	2.46
11	River	0.92	0.90	0.93	0.95	-0.27	0.29	0.93
12	Water body	0.93	0.95	0.92	0.96	0.65	-0.28	1.03
	Overall	0.74	0.83	0.86	0.88	4.51	6.61	7.92

a Spectral features only   *d* Spectral + Ent17

b Spectral + *Mean* 9   *c* Spectral + *Con9*

z_{xa} *Z*-statistic with respect to *a* (*x* varies from *b* to *d*)

A global threshold based region growing segmentation was implemented for urban classification. Segment-based classifications were also carried out using GML and RPROP approach. Segment-based classification showed significant improvement over the per-pixel approach. Table 2 shows comparison of classification results for Lucknow study site between per pixel GML classification and segment-based classification.

Table 2 Comparison of per-pixel and segment-based classification for Lucknow study site

S. no.	*Class Name*	*Training*			*Test*		
		a	*b*	z_{ba}	*a*	*b*	z_{ba}
1	Agriculture-1	0.65	0.61	-0.24	0.74	0.79	0.29
2	Agriculture-2	0.61	0.99	5.60	0.73	0.75	0.15
3	Commercial	0.42	0.99	8.29	0.45	0.98	6.87
4	Educational institutes	0.44	0.88	5.05	0.49	0.90	4.67
5	Government establishment	0.15	0.90	9.04	0.05	0.90	11.17
6	Grassy land	0.87	1.00	3.03	0.87	1.00	2.78
7	High residential	0.80	1.00	4.48	0.75	1.00	5.17
8	Medium residential	0.81	1.00	3.89	0.74	1.00	5.13
9	Park	0.68	1.00	6.20	0.69	0.96	2.87
10	Reserve forest	0.94	0.70	-3.26	0.91	0.70	-2.78
11	River	0.95	1.00	1.24	0.92	1.00	2.77
12	Water body	0.84	0.98	1.35	0.92	0.98	0.73
	Overall	0.68	0.93	7.26	0.68	0.92	6.60

a- per-pixel GML
b- segment-based GML

Therefore, while a making a comparison of all the techniques tested above, It can be concluded that the higher classification accuracy was achieved using RPROP and with the inclusion of spatial properties in the classification process. Although this increase in accuracy was statistically not significant in case of RPROP but with inclusion of spatial information using window-based texture and per-segment approach this increase was statistically significantly higher and classification image obtained as a result of segment-based classifications looked more like a thematic map while making a comparison with results of per-pixel approach.

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