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"SEMI-AUTOMATIC EXTRACTION OF TOPOGRAPHICAL DATABASE FROM HIGH RESOLUTION MULTISPECTRAL REMOTE SENSING DATA"

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Abstract:

Owing to the advancement in the field of Geoinformatics, automatic or semi-automatic extraction of features from maps and images is the need of the hour, its importance being efficient upgradation of topographic databases. In this study, topographic features of Indraprastha, New Delhi have been semi-automatically extracted from high resolution WorldView-3 multispectral data. The study was implemented in the following seven steps:

Step 1: Perform multiresolution image segmentation in eCognition to evaluate the parameters of scale, shape, compactness and layer weights of the image by hit and trial method.

Step 2: Apply appropriate rule sets to extract the major features, such as water and vegetation, based on their distinct spectral properties.

Step 3: Employ nearest neighbour analysis and morphological operations to extract the remaining features.

Step 4: Performing morphological operations helped in masking features with a particular shape.

Step 5: Perform accuracy assessment of the object based classification and generating an error matrix in eCognition.

Step 6: Manually digitize images in ArcGIS Desktop.

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Perform supervised and unsupervised classification, and their accuracy assessment in ERDAS Imagine.

Step 7: Perform pixel by pixel analysis of the different classifications using Harris ENVI.

By performing these steps, the following accuracy levels were obtained:

1. Threshold classification - 92.32%
2. Supervised classification - 74.00%
3. Unsupervised classification - 82.00%
4. Pixel to pixel accuracy analysis between manually digitized image and -
   a. threshold classification image - 59.4098%
   b. supervised classification image - 58.2857%
   c. unsupervised classification image - 57.9397%

And we could conclude that:

1. Multiresolution segmentation and rule based classification worked well for voluminous and prominent features; however, small features could only be extracted using Nearest Neighbour Classification.

2. With the availability of a DSM Layer, extraction of high rise features would have been easier.

3. Results obtained from object-based classification are accurate for feature extraction.

Keywords: Topographic Database**,** Semi-automatic Extraction, Multiresolution Segmentation, Threshold Classification, Nearest Neighbour Analysis, Pixel-by-pixel Analysis.

1. Introduction

Rapid urbanisation is a spatial cause which has led to changing scenario of the existing topography. With advancement in the field of Geoinformatics, large amount of data in this regard has been generated, and traditional topographic database consisting of aerial photographs and methods such as photogrammetry can no longer be relied upon, and thus, require drastic upgradation. Very High Spatial Resolution Data and object-based feature extraction methods offer promising replacements. And while much work has been done on developing and applying these newbies, very less work has been produced to show the interconnectivity between the variety of datasets, the geographical area under consideration and the method of feature extraction by using semi-automatic feature extraction methods**.**

In this study, we have attempted to perform semi-automatic topographic feature extraction of high resolution multispectral data of Indraprastha, New Delhi obtained from WorldView-3 based on image segmentation and threshold classification.

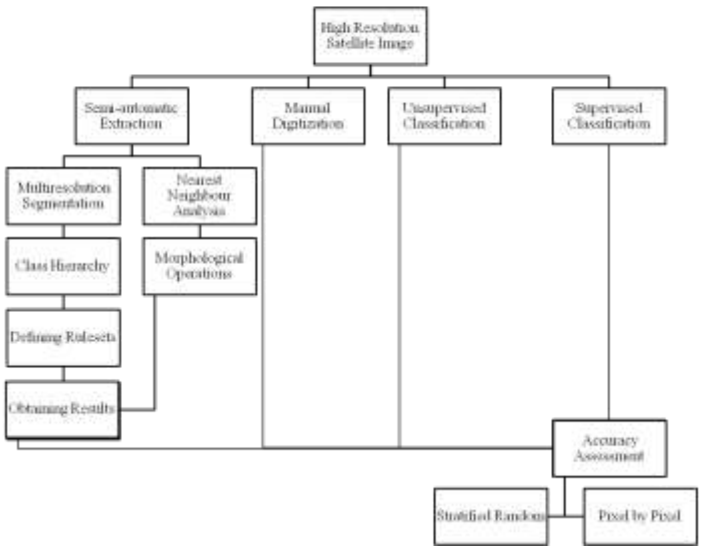
2. Study Area

The capital of India has a dynamic landscape and landuse pattern, making the area a complex one. Thus, for the purposes of this study, we have taken into consideration Indraprastha Metro Station and its adjoining areas, the diverse landscape of which includes the river Yamuna, the wide M.G. Marg road, a large thermal power plant, small hutments and some vegetation, making it the ideal study area for our model.

The geographical coordinates of the study area lie between 3168327.6 N to 3167690.4 N and 718971 E to 720407.1 E. The environments of all the data sets were set to the Geographic Coordinate System of Datum, WGS_1984, and Projected Coordinate System of Universal Transverse Mercator for Zone 43. A high-resolution WorldView3 image raster captured in 2015 was used as the input. The bands available in this image were Blue, Green, Red and Near InfraRed.

Figure 1: Study Area

3. Methodology



The major classes constructed in Class Hierarchy include big buildings, small buildings, metro track, parking, railways, road, water, grassland, open land, vegetation and shadow. Thereafter, the image is segmented using multiresolution segmentation algorithm, setting the parameter of scale at 100, and shape and compactness at 0.9 and 0.3 respectively. Subsequently, rules for extraction of water and vegetation are made in the process tree by setting NDVI>0.23 for vegetation and NIR<258 for water. Since transportation lines and buildings have similar spectral properties, we extracted these using nearest neighbourhood classification and used sample training sets. Thereafter, classification algorithm was used, and then, the active classes were selected and executed. Subsequently, in algorithm parameter, 'open image object' was chosen as morphology algorithm to mask building of square shape

4. Results and Discussion

4.1 Results for Multiresolution Segmentation

We conducted multiresolution image segmentation by taking different parameters and values as detailed above, and then visually interpreted the segmented image to find out how close the segmented boundaries were to the actual boundaries of the objects.

4.2 Rulesets

Rulesets were created taking into consideration the spectral, contextual and spatial properties of the objects to be extracted. We used NDVI for extraction of vegetation classes and Mean NIR for extracting of waterbodies.

4.3 Threshold

After proper extraction parameters were selected, it was the time to choose the best fit values. Threshold values were taken after continuous testing of various values, thereby finally settling down for the best one.

4.4 NN

Manmade structures and different types of vegetation, by virtue of having similar spectral reflectance, could not be separated using a rule set. Their extraction required the deployment of Nearest Neighbour algorithm, which is a form of supervised classification.

4.5 Morphological Operations

Morphological operations were performed so that the different buildings could be separated out based on their shape, so as to enhance the image, ease the classification process, and achieve higher accuracy levels.

4.6 Results for Accuracy Assessment

Accuracy assessment was carried out in two steps - in the first, random points were taken for finding out accuracy in ERDAS IMAGINE. And in the second, pixel by pixel accuracy was found out using ENVI. We created an error matrix in eCognition which enabled us to assess the accuracy of our object based classification, 92.32 %.

4.6.1 Results for Unsupervised Classification and Accuracy Assessment

60 clusters and 200 'stratified random' points were taken. Accuracy achieved was 82.00%.

4.6.2 Results for Supervised Classification and Accuracy Assessment

20 training sets of each class and 200 'stratified random' points were taken. Accuracy achieved was 74.00%.

4.6.3 Results for Pixel by Pixel Analysis

We utilized the capabilities of ENVI to compare the manually digitised image with the image classified in eCognition. Between the manually digitised image and the threshold classification image, accuracy obtained was 59.4098% and that between ground image and supervised image and unsupervised image, it was 58.2857% and 57.9397% respectively, thereby proving that object based classification performed using eCognition is the most accurate method for extraction different kinds of features.

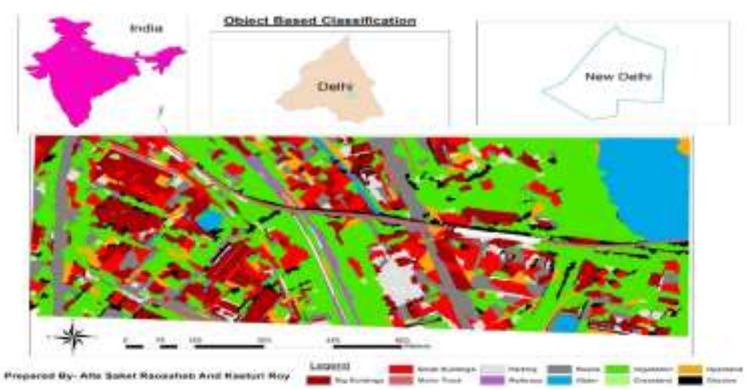


Figure 2: Results of Semi-automatic Extraction

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Table 1: Accuracy Assessment in eCognition

Overall Accuracy = 92.32% Kappa Coefficient = 0.912		
Classes	**Producer's Accuracy**	**User's Accuracy**
Big Buildings	97.02%	100%
Small Buildings	96.74%	100%
Metro Track	92.3%	100%
Parking	100%	100%
Railways	78.57%	100%
Roads	100%	98.78%
Water	100%	100%
Vegetation	100%	37.97%
Grassland	7.69%	100%
Openland	96.77%	100%
Shadow	100%	100%

Table 2: Accuracy Assessment using Stratified Random Sampling of Supervised and Unsupervised Classification

Classes	**Supervised Classification**		**Unsupervised Classification**	
	Overall Accuracy= 74.00% Kappa Coefficient=0.6483		Overall Accuracy= 82.00% Kappa Coefficient= 0.7554	
	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy
Unclassified	-	-	-	-
Water	85.71%	100.00%	92.86%	92.86%
Vegetation	100.00%	77.65%	95.52%	95.52%
Builtup	73.77%	71.43%	75.68%	82.35%
Shadow	22.73%	83.33%	64.00%	69.57%
Openland	29.17%	33.33	37.50%	20.00%

Table 3: Accuracy Assessment using Pixel by Pixel method of Supervised and Unsupervised Classification

Classes	**Supervised Classification**		**Unsupervised Classification**	
	Overall Accuracy= 58.29% Kappa Coefficient= 0.4362		Overall Accuracy= 57.94% Kappa Coefficient= 0.4466	
	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy
Unclassified	-	-	-	-
Water	77.65	95.28	83.19	87.02
Vegetation	97.68	63.59	90.84	74.70
Builtup	66.92	64.67	72.74	65.62
Shadow	22.01	32.01	48.50	18.31
Openland	17.70	24.68	10.16	17.11

Table 4: Accuracy Assessment using Pixel by Pixel method of Object Based Classification

Overall Accuracy 59.41% **Kappa Coefficient** 0.4897		
Classes	**Producer's Accuracy**	**User's Accuracy**
Buildings	72.76%	46.30%
Metro Track	74.96%	54.53%
Parking	37.00%	49.10%
Railways	42.38%	72.62%
Roads	61.04%	38.57%
Water	92.74%	96.76%
Vegetation	87.23%	66.85%
Openland	11.31%	49.75%
Shadow	44.77%	43.44%

Conclusion

From the findings of this project, we could say that:

i. Object based classification method is very useful and effective for the detection and extraction of various features, majorly because it takes into consideration both, spectral and spatial properties, unlike supervised or unsupervised classifications, where we consider only the spectral information.
ii. While the NDVI method is best suited for the extraction of Vegetation, different kinds of vegetation have different threshold values for extraction, and therefore was separated using the NN classification.
iii. NDWI cannot be always used for the extraction of water bodies, especially when the image has a lot of shadows.
iv. The process of classifying a high resolution data would have been much easier if the true ortho image of the area could have been obtained.
v. The segments formed in the image may or may not correspond to the actual boundaries of features in the image, i.e., at places, very small buildings might have got mixed up with the vegetation cover.
vi. The understanding of visual interpretation keys such as shape, size, texture, shadow, association and colour is necessary for such analysis.
vii. Morphological operations help in masking out features of a similar size.
viii. Detection of very small features is difficult with these algorithms.
ix. Framing of rule sets can be difficult as not all features respond equally to the parameters.
x. eCognition is an easy to use and handy software.
xi. Accuracy obtained from object based classification is very high, especially in the case of water and dense vegetation.
xii. For deriving higher accuracy of structures such as buildings, metro track, etc, the DSM layer should be used.
xiii. Pixel by Pixel Analysis is the most appropriate methodology for accuracy assessment out of all that we have analysed in this project.

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