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An object based building extraction method and classification using high resolution remote sensing data

Neeti SHRIVASTAVA[1,*], Praveen Kumar RAI[2]

[1] Indian Institute of Remote Sensing, Dehradun, Uttrakhand, India
[2] Department of Geography, Banaras Hindu University, Varanasi-221005, Uttar Pradesh, India
* *Corresponding author*, neeti.iirs@gmail.com

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Abstract

The increasing availability of the high spatial resolution satellite images has provided a new data source for building extraction. This paper proves the concept of object oriented classification using high-resolution satellite data (Cartosat-1 satellite data fused with IRS-1C, LISS IV data) for automatic building extraction using eCognition software. In this study, the overall accuracy of classified image is 0.94 and Kappa accuracy is 0.92. The producer accuracy for building, vegetation and shadow are 0.9745, 1.0 and 0.8999, respectively, whereas user accuracy for building, vegetation and shadow are 1.0, 0.9475 and 1.0 respectively. The classification overall accuracy is based on TTA mask (training and test area mask) and it is 0.98 and Kappa accuracy is 0.96. The producer accuracy for building, forest and shadow are 1.0, 1.0 and 0.7344, respectively and user accuracy for building, vegetation and shadow are 1.0, 0.9475 and 1.0, respectively.

Keywords: *spatial filter, object oriented fuzzy classification, high resolution data, overall accuracy, producer accuracy*

Rezumat. O metodă de extragere a clădirilor orientată obiect și clasificare folosind date de înaltă rezoluție furnizate de teledetecție

Disponibilitatea tot mai mare a imaginilor satelitare de înaltă rezoluție reprezintă o sursă nouă și importantă pentru extragerea automatăa clădirilor. Prezenta lucrare demonstrează conceptul de segmentare şi clasificare orientată-obiect, folosind date satelitare de înaltă rezoluţie (date Cartosat-1 combinate cu IRS-1C, LISS IV) pentru extragerea automată a clădirilor folosind softul eCognition. Acurateţea generală a imaginii clasificate este 0,94, iar acurateţea Kappa este 0,92. Acurateţea producătorului pentru clădiri, vegetaţie şi umbră este de 0,9745; 1,0 şi 0,8999, iar valorile utilizatorului pentru aceleaşi elemente sunt de 1,0; 0,9475 şi 1,0. Acurateţea generală a clasificării este bazată pe masca TTA (suprafaţa de pregătire şi testare) şi este de 0,98, iar acurateţea Kappa este de 0,96. Acurateţea producătorului pentru clădiri, vegetaţie şi umbră este de 1,0; 1,0 şi respectiv, 0,7344, iar valorile utilizatorului pentru aceleaşi elemente sunt de 1,0; 0,9475 şi, respectiv, 1,0.

Cuvinte-cheie: *filtru spaţial, clasificare fuzzy orientată-obiect, date de înaltă rezoluţie, acurateţe generală, acurateţe producător*

Introduction

Building extraction from high-resolution remote sensing images has been an important research topic for recent decades. The extraction of building information from high-resolution imagery has been one of the most interesting topics for remote sensing and computer vision scientists. Object-based image analysis (OBIA), or geographic object-based image analysis, is an emerging field resulting from new earth observation techniques and concepts, and has received considerable impetus over the last decade (Blaschke, 2010). In contrast to traditional pixel-based analysis, OBIA uses regions or segments of an image as basic units. This offers several benefits, including reduced spectral variability and more spatial and contextual information such as shape and topological relationships (Blaschke, 2010).

In our country, urban areas are rapidly changing mainly due to human activities in construction, destruction of topographic elements such as buildings and roads. These changes in urban environment enforce updating of old records, which can help planners to have accurate building zones for urban planning, maintenance and development (Pandey 2004). The main problem encountered in building extraction approaches is the confusion of the building class with other object classes, such as shadows, vegetation, and the ground. The detection of a non-building as a building and mixture of trees and shadows are examples of other misclassification problems. These misclassification problems, which are attributable to a single data set and method, have a negative effect on the accuracy of the classification process. For this reason, different approaches and methods have been proposed to solve the problems caused by the complexity of classification process (Uzar, 2014).

Building detection from high-resolution satellite images has attracted great attention in recent years. To automate the process and produce reliable, precise, and complete data sets, multiple data sources and advanced techniques should be used (Lee et al. 2003). These methods are mainly based on edge detection, line extraction and building polygon generation. Several approaches have used the building models to facilitate and automate the building extraction procedure (Tseng & Wang 2003).

Most of the recent work on building extraction from high-resolution satellite images is based on supervised techniques. Either these techniques require a digital image processing classification method based on initial training data to provide hypotheses for the positions and sizes of the candidate building features (ZuWhan & Nevatia 1998; Benediktsson et al. 2003), or they use

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training sets or model databases to classify or match the buildings (ZuWhan & Nevatia 1999; Segl & Kaufmann 2001). Classification technique is then applied into these homogenous regions taking the shape, texture and spectral properties of the regions (Rizvi and Mohan, 2012). Supervised classification is one of the most commonly undertaken analysis of remotely sensed data. The output of a supervised classification is effectively a thematic map that provides a snapshot representation of the spatial distribution of a particular theme of interest such as land cover. The goal of a supervised image classification system is to group images into semantic categories giving thus the opportunity of fast and accurate image search (Rizvi and Mohan, 2010).

Automatic building and road extraction algorithm can reduce both time and labour to construct and update the road spatial database in such applications. However, fully automated algorithms to recognize them for applications where accuracy is critical are very difficult (Jeon et al. 2002, Tupin et al. 2002, Chaudhuri et al. 2012 and Teng et al. 2014). Sohn and Dowman (2001) extract the polygon of building based on Fourier Transform and Binary Space Partitioning tree and combined with Building Unit Shape knowledge. Stassopoulou (2000) combines multi-scale region segmentation based on canny operator with edge segmentation to extract regional features (geometry shape, radiation characteristic, context information), and extracts building features by Bayesian network.

Remote sensing is of great importance to be used in collecting geographical data and huge remote sensing images have been rapidly increasing. The high-resolution remote sensing images are vital for the fields of national defense, disaster relief and so on (Bruzzone et al., 2006). The automated or semi-automated analysis of the satellite images is obstructed by the high complexity of such images (Gupta and Bhadauria, 2014). The datasets obtained from different satellite sensor systems create the opportunity for development of methods to extract objects (Baltsavias, 1999; Tarsha-Kurdi, 2007; Matikainen, 2009; Rotteinsteiner et al., 2012). Regarding the data source, due to the limitations of using single-source data, the integration of multi-sensor data is desired because this method preserves the many advantages of the involved data sets (Gruen, 2008; Kwak et al., 2012).

Segmentation of the images is carried out using the region-based algorithms such as morphological marker based watershed transform by employing the advantages of multi-resolution framework and multiscale gradient algorithms. Problems and difficulties appear when extracting the objects with high local variance context and spectral signatures disturbances (Lhomme et al. 2004). Thus, the extraction methods should be adapted to these new images.

Improvement of per-pixel classification is based on the introduction of semantic information. The main goal is to improve building borders delimitation. The information on spatial relations between the different land cover types can be used to improve per-pixel classifications. Different methods, more or less complex, have been recently developed (Teffelen et al, 2001, Bianchin et al, 2003 ; Van De Voorde et al, 2003).

The main objective of this paper is the extraction of buildings from high-resolution imagery.

Study area

The study area is a part of the administrative area of BHEL (Bharat Heavy Electrical Limited) colony, Haridwar, Uttrakhand. BHEL is the largest engineering and manufacturing enterprise in India in the energy-related infrastructure sector today. BHEL was established more than 40 years ago, being founded in 1950s. Location map of the study area is shown in Figure 1.

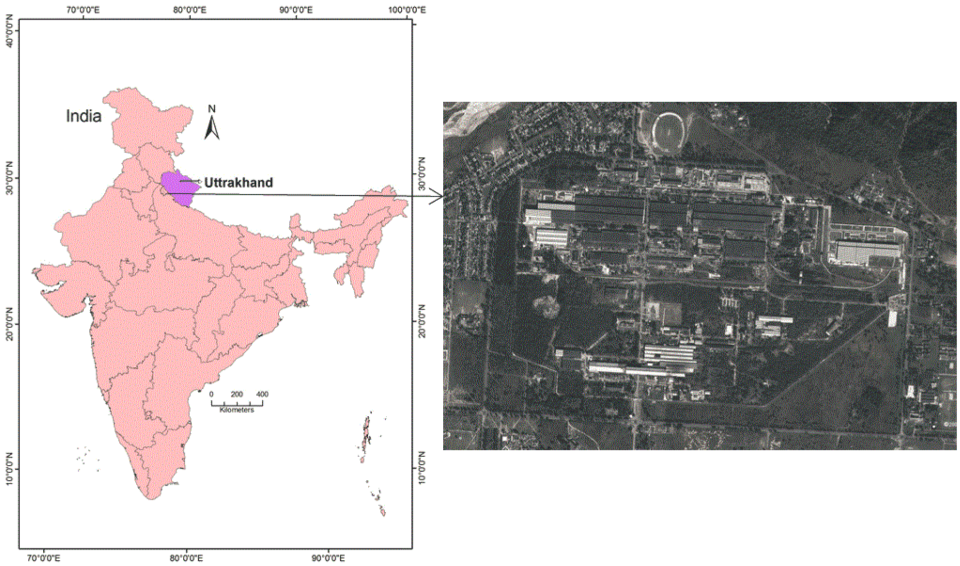

Fig. 1: Geographical location of the study area in Haridwar district, Uttrakhand (India) in satellite data

Data used and methodology

In this study, remote sensing & GIS software i.e. Erdas Imagine (ver. 10), Definiens Developer (new version of eCognition) and ArcGIS (ver. 9.3) were used. MS Office was also used for this study for the data analysis. The Cartosat-1 and LISS IV satellite data were used for this study. Satellite data used in this study is georeferenced with UTM-zone 44 projection system and WGS-84 datum. A brief description of the payload and the other mainframe elements of Cartosat-1 are given in the Tables 1 and 2.

Table 1: Orbit specifications of Cartosat-1

No.	Orbit Characteristic	Specification
1	Nominal altitude	617.99 km
2	Number of orbits per day	15
3	Orbital repeativity cycle	116 days
4	Local time for Equatorial crossing	10:30 am
5	Orbital parameters: a) Semi major axis b) Eccentricity c) Inclination	 6996.12 km 0.001 97.87 degree

Table 2: Cartosat-1 payload specification

No.	Parameter Name	Specification Fore (+26 deg) and Aft (-5 deg)
1	Spatial resolution: GIFOV (across-track × along track)	2.5 × 2.78 m (Fore); 2.22 × 2.23 m (Aft)
2	Spectral resolution: a) No. of bands b) Bandwidth	 1 Panchromatic 500 nm to 850 nm
3	Radiometric resolution: a) Saturation radiance b) Quantization c) SNR	55mw/cm*cm/str/ micron 10 bits 345 at saturation radiance
4	Swath (stereo) Fore + Aft combined (mono)	30 km 26.855 km
5	CCD parameters: a) No. of detectors / elements b) Detector element size c) Odd-Even Spacing	 12,000 per camera 7 × 7 microns 35 microns staggered
6	Optics: a) No. of mirrors b) Effective focal length (mm) c) F-Number d) Field of view (degrees)	 3 1980 F/4.5 +/- 1.08
7	Integration time (ms)	0.336
8	Nominal B/H ratio for stereo	0.62

Definiens Developer software mainly works on the concepts of object oriented classification and also works on the multiresolution segmentation. The image is segmented for the classification of different urban areas. Classification was done using specific sets of rules. In this software, classification is conducted by fuzzy logic. The segmentation was done at varying resolutions. This image segmentation technique is called multiresolution segmentation. This segmentation algorithm was applied on the image so that the similar kind of pixels from groups according to the applied homogeneity criteria. Thus based on the homogeneity criteria, the objects were formed by merging the pixels falling under the criteria.

The process of automatic feature extraction is mainly divided in to three parts: (a) image processing, (b) information extraction using spatial filtered, (c) information extraction using fuzzy rule base classification.

The Cartosat panchromatic image of the study area was fused with the multispectral images with the help of Brovey transformation and nearest neighbourhood method. Details of methodology for automatic features extraction is given in the Figure 2.

Two processes are used for automatic feature extraction in the study area: (a) spatial filtering and (b) object oriented fuzzy classification.

Fused Image

Multiresolurion segmentation

Classification based on segmentation

Automatic extraction of buildings

Export the buildings features

Accuracy assessment

Fig. 2: Flow chart of automatic feature extraction

Spatial filtering refers to the altering of spatial or spectral features for image enhancement. Convolution filtering is the process of averaging small sets of pixels across an image. Convolution filtering to used to change the spatial frequency characteristics of an image (Jensen 1996).

The fused image is filtered using the different high pass filters like Kirsch, Laplace, Prewitt, Sobel, Canny filtered images (Fig. 3 a-e). These filters are used for detection of the edges, but were not found appropriate for the study area; hence this method is discarded and another approach is used which is suitable for detection of edge.

Multiresolution segmentation is a new procedure for image object extraction. It allows the segmentation of an image into a network of homogeneous image regions at any chosen resolution (Pandey 2004; Dell'Acqua & Gamba 2007). These image objects primitives represent image information in an abstracted form, serving as building blocks and information carriers for subsequent classification. Beyond purely spectral information, image objects contain a lot of additional attributes, which can be used for classification: shape, texture and operating over the network a whole set of relational/contextual information.

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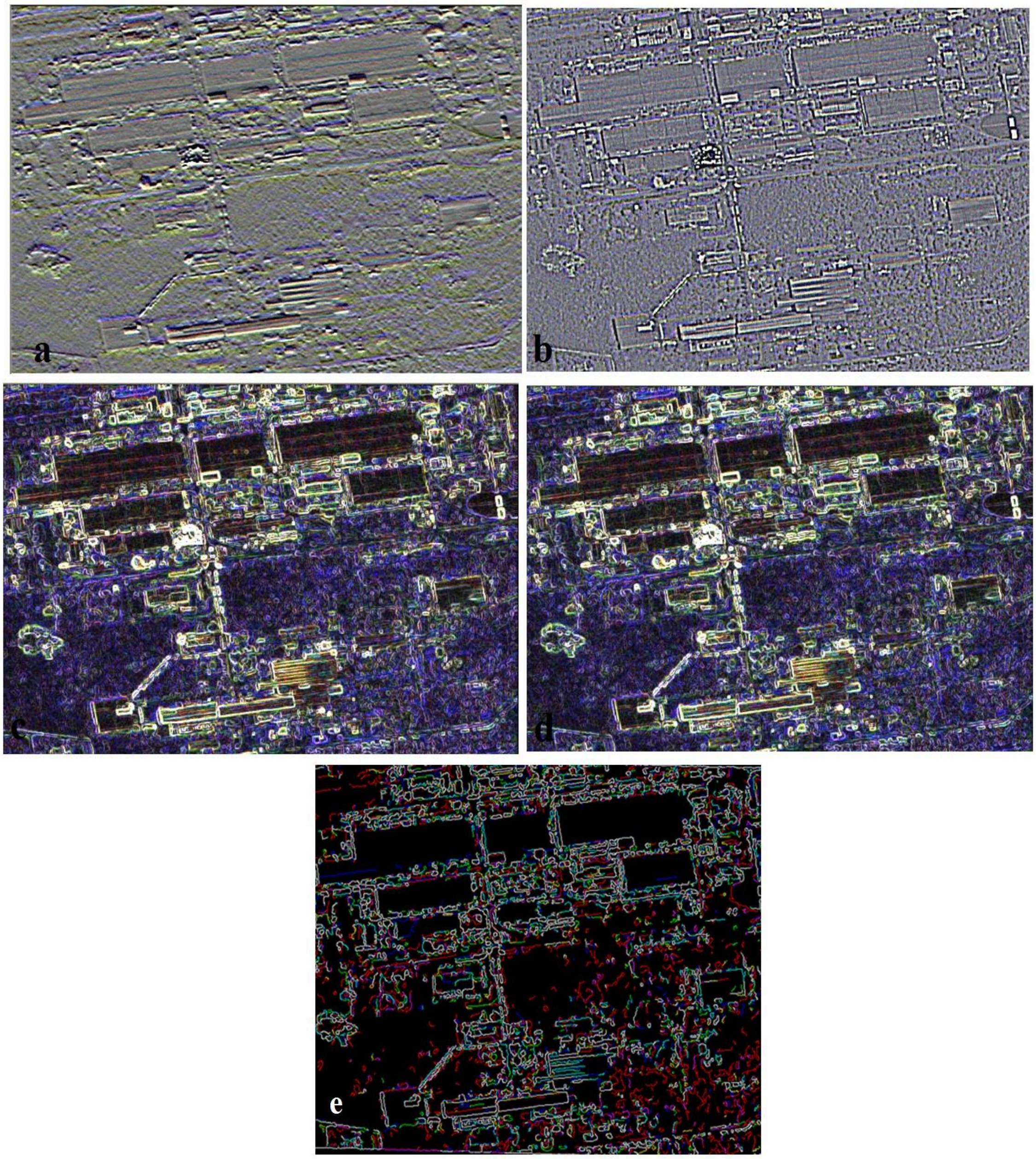

Fig. 3 (a-e): Filtered images (Kirsch, Laplace, Prewitt, Sobel, Canny filtered images)

Results and discussion

Multiresolution segmentation

In this study, fused image of Cartosat-1 was segmented using Definiens Developer. In context of the building extraction, segmentation is carried out to adjust scale parameter, shape factor and compactness. These parameters should be adjusted so that the process gives the homogeneous region with defined boundary of the object of interest. Once these parameters ratios are adjusted into homogeneous pattern, different rules can be implemented using fuzzy rule base for feature extraction.

Table 3 shows the parameters used for segmentation. By using scale parameter 17 and homogeneity criterion (Shape factor 0.2, Compactness 0.4), 660 no. of object were identified and similarly by taking scale parameter 30, shape factor 0.2, compactness 0.5, 460 no. of object were identified and when scale parameter 40 was used, shape factor was 0.3, compactness was 0.5, then 102 no. of object were identified. Process of segmentation by scale parameters 17, 30 and 40 are given in the Figures 4, 5, 6 respectively.

Table 3: Parameters used for segmentation

Scale parameter		17	30	40
Homogeneity criterion	Shape factor	0.2	0.2	0.3
	Compactness	0.4	0.5	0.5
	No. of objects	660	460	102

By taking scale parameter 17 and homogeneity criteria (shape factor 0.2, compactness 0.5), the objects are lying inside building area in segmented image. This shows that these parameters are better for building extractions (Fig. 4).

There are different parameters used for deciding the homogeneity criteria for the image segmentation. Multiresolution segmentation was done at different scale parameters. The scale parameters determine the size of the objects formed during segmentation.

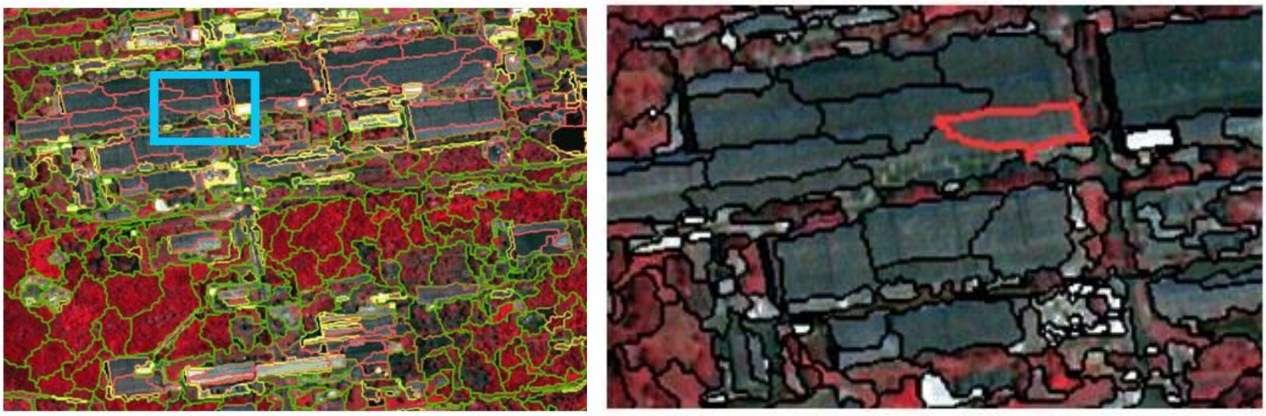

Fig. 4: Result of segmented image by scale parameter 17

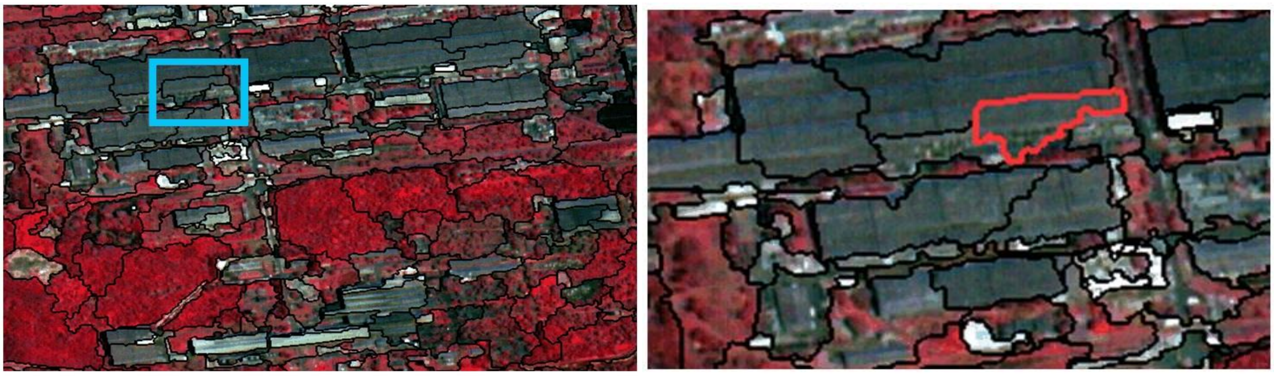

Fig. 5: Result of segmented image by scale parameter 30

By taking scale parameter 30 and shape factor 0.2, compactness 0.5, the objects of interest are lying outside the building area boundary. By which it can be analysed that this parameters is not very much suitable for building extraction.

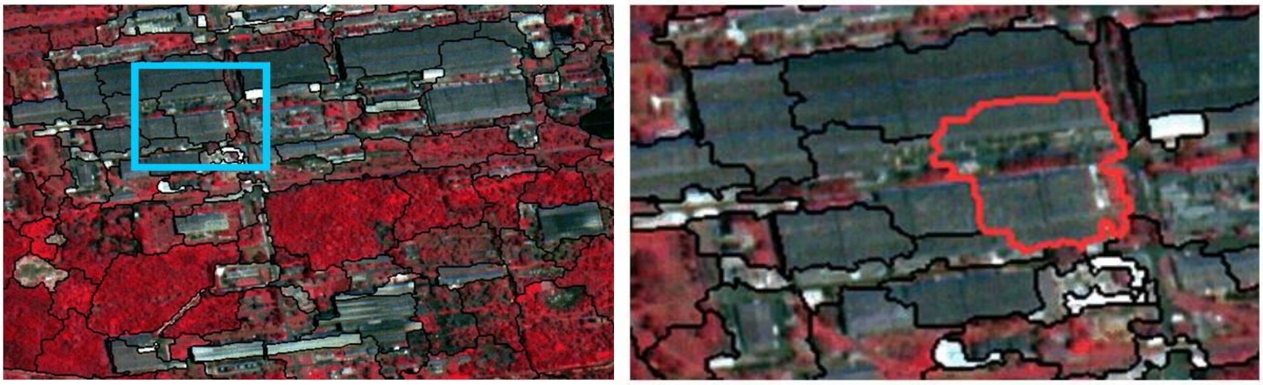

Fig. 6: Result of segmented image by scale parameter 40

By taking scale parameter 40, shape factor 0.3, compactness 0.5, the objects are lying outside of area of interest. This scale parameter is very helpful for extraction of big object like large building (Fig. 6).

Throughout the image segmentation, the whole image is segmented and image objects are generated based on several adjustable criteria of heterogeneity in shape. By modifying the value of the scale parameter, the size of the resulting image objects varies. A high scale parameter result in large objects and vice-versa. After segmentation, the image is classified based on object–oriented approach. This process of classification of objects has been done using an export knowledge base, which is inbuilt function of Definiens Developer. The fuzzy classification method takes into account that there are pixels of mixed makeup, that is, pixels cannot be definitively assigned to one category. "Clearly, there is a real need to be a way to make the classification algorithms more sensitive to the imprecise (fuzzy) nature of the real world" (Jensen 1996). Fuzzy classification works using a membership function, where in a pixel value it is determined by whether it is closer to one class than to another. A fuzzy classification does not have definite boundaries, and each pixel can belong to several different classes (Jensen 1996).

Corresponding to the rule and the knowledge, the membership values and multiresolution fuzzy curves were defined. Different curves describe how the membership value for a specific expression is assigned and calculated for a certain feature values of image objects.

Accuracy measurement

Quantitative assessment is calculated on the area accuracy bases. It defines the accuracy in extraction in the area, the difference in reference and extracted data.

Area accuracy = Area extracted (sq. m) / Area extracted (sq. m) × 100

Table 4: Number of buildings and difference error

No. of building	Difference error (%)
1	1.09
2	0.10
3	-3.86
4	6.89
5	14.90
6	-2.40
7	7.71
8	13.86
9	12.7
10	14.20
11	7.08
12	-5.27
13	-3.23
14	-12.25

Number of building and percentage of difference error is shown in Table 4. The maximum difference error, 14.90%, corresponds to no. of building 5, followed by no. of building 10 with 14.20% difference errors. No. of building 3, 6, 12, 13, 14 show percentage difference error in negative trend, in which no. of building 14 shows minimum -12.25% difference error.

Classified Image Output

After performing the classification process, the classified image has been developed (Fig. 7). When export the building from classified image, only the feature of interest i.e. buildings were generated.

Overall accuracy of classified image is 0.94 and Kappa accuracy is 0.92. The produced accuracy for building, vegetation and shadow are 0.9745, 1.0 and 0.8999 respectively.

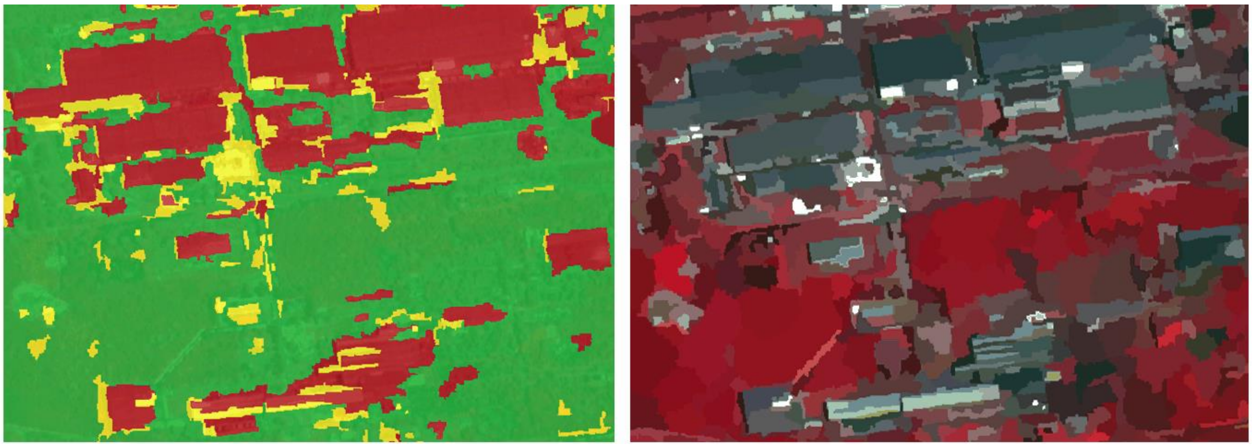

Fig. 7: Classified image after fuzzy classification and its accuracy

Overall classification accuracy based on TTA mask (training and test area mask) is calculated. Classification overall accuracy is 0.98 and Kappa accuracy is 0.96. The producer accuracy for building, vegetation and shadow are 1.0, 1.0 and 0.7344 respectively and user accuracy for building, forest and shadow are 1.0, 0.9475 and 1.0 respectively.

Conclusion

In this study, an approach was developed to extract the buildings from high resolution satellite images with the use of image classification.

The steps followed in this study gave satisfactory result when compared to the original digitized vector layer. But the clear edges of the buildings are not extracted; it coincides with the original image. So that it can also be considered as the urban buildings. The feature extracted using the methods, which are not matching, can also be considered because they are at location and it can be considered as the footprints of the buildings. The edges of the building are extracted using the different high pass spatial filter but edges are not very sharp. So these images are to be thinned using some thinning algorithms. Using automatic extraction techniques, there is a scope on the thinning of the edges of urban buildings extracted.

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