FAST ICA BASED ALGORITHM FOR BUILDING DETECTION FROM VHR IMAGERY

Lipika Agarwal, K. S. Rajan

International Institute of Information Technology
Lab for Spatial Informatics
Hyderabad-500032, India

ABSTRACT

In the recent past there is increased interest in detection and extraction of buildings using object based approaches on given high to very high resolution imagery. In this paper, we introduce a new unsupervised approach to detect buildings from the very high resolution (VHR) multispectral satellite image. Independent component analysis (ICA) followed by Otsu thresholding is used for extraction of multicoloured buildings of diversified size and shape. QuickBird image of Legaspi city has been used to analyze the technique and detection results obtained from three subset images indicate average detection percentage of 84.35 % along with 38.19 % branch factor value. Object-level evaluation results give 72.48% for fully detected buildings count.

***Index Terms*—** Building detection, independent component analysis, pan-sharpened imagery, VHR image

1. INTRODUCTION

The automatic building detection and extraction is one of the most challenging research areas of remote sensing. It is widely used in many applications such as urban planning, cartography, environment modeling, illegal construction analysis, military applications and disaster management. Challenges associated with remote sensing applications using high resolution satellite imagery include height discontinuities, shadows and mixed pixels. Conventional pixel based classification techniques can not be used to overcome these challenges.

Previous work in this area includes building detection using Panchromatic, LiDAR [1], [2], SAR [1], multispectral data etc. QuickBird, GeoEye, Cartosat and other satellites/ sensors provide metre to sub-metre resolution image products. Different products result in their suitability for detection of different classes such as settlement areas, agriculture, water bodies. The focus of the work is building detection using multispectral satellite images.

Supervised learning using manually marked classes or trained datasets is a widely used technique in previous literature for object detection in satellite imagery. Typically color, texture and size are the key factors considered while segmenting out buildings. SVM based supervised classification of the four spectral bands, normalized difference vegetation index (NDVI), local variance, and morphological profile into vegetation, water, roads, shadows, and several types of buildings has been done in [3]. Other methods mentioned in [3] include mean shift algorithm, multi-resolution segmentation, masking out shadows, water, vegetation using thresholding, marker based watershed segmentation, classification based on object geometry, brightness values. Contextual information of shadows has been used in [4], [5] and [1]. Segmentation based on seeded region growing algorithm using structural and spectral information of the image has been reported in [5]. PCA also leads to object segmentation but with unclear boundaries which requires alot of post-processing while ICA decomposition gives defined boundaries of objects.

In this paper, an unsupervised classification technique, ICA decomposition has been applied to image components to obtain mutually independent classes of image. Experimental results show that ICA can be used to classify buildings from non building areas.

Details of the dataset used in the analysis are mentioned in section 2. The methodology is discussed in section 3 followed by results in section 4 and conclusion in section 5.

2. DATASET

QuickBird image of Legaspi city [3] is used to evaluate the performance of the proposed building detection algorithm. The data contains Panchromatic band of 1668×1668 pixels with 0.6 m spatial resolution and multispectral band with four spectral bands of 2.4 m spatial resolution and 418 x 418 pixel size. The dataset contains buildings having large variation in size, shape and color as well as other classes such as vegetation, roads and other objects like vehicles.

3. METHODOLOGY

3.1. Pre-Processing

High resolution image is essential to improve the detection accuracy. Resolution of multispectral image is enhanced by

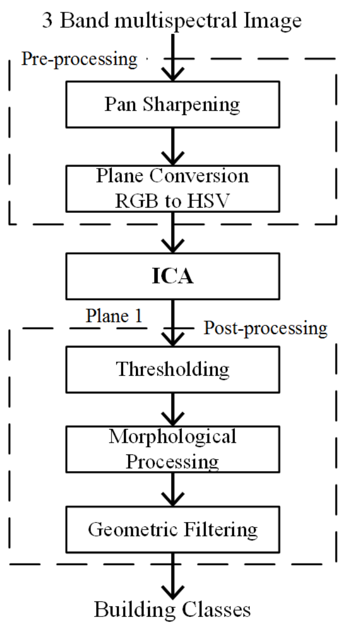


Fig. 1: Flow chart of the process

fusing it with panchromatic image to obtain pan resolution. This pan-sharpening process is performed using ENVI 4.8 software and the pan-sharpened image is shown in Fig. 3a.

3.2. Independent Component Analysis

Independent Component Analysis is a widely used technique for blind source separation. It gives the approximate statistical independence of resulted components. The principle of ICA works on minimizing mutual information. It generates source components which are independent of each other and have zero mean from the observed mixed components. Here we present a brief overview of ICA model [6].

Independent Component Analysis (ICA) has been used in cocktail-party problems [6], face recognition [7], denoising and decomposition of biomedical signals [8] etc. In this paper we have presented application of ICA in extracting buildings.

The ICA model [6] can be expressed as,

$$\mathbf{x} = \mathbf{A}\mathbf{s} \tag{1}$$

where $\mathbf{x}$ is the random vector whose elements are in the n dimensional observed planes x_1,x_2...x_n. $\mathbf{A}$ is the mixture matrix and $\mathbf{s}$ is the random vector of independent components, s_1,s_2...s_n. All we observe is the random vector $\mathbf{x}$, and we must estimate both $\mathbf{A}$ and $\mathbf{s}$. The objective of ICA is to find a matrix $\mathbf{W}$, which is inverse of $\mathbf{A}$, that linearly converts the vector $\mathbf{x}$ such that the components of the converted new vector $\mathbf{y} = (y_1, y_2, \dots y_n)^T$ are as independent of each other as possible, i.e.

$$\mathbf{y} = \mathbf{W}\mathbf{x} \tag{2}$$

In this paper we have used fast ICA algorithm. Multispectral RGB bands are first transformed to HSV bands and the H, S, V bands are considered as observed components having mixed information. ICA is applied on these components and three output source components, S_1, S_2, S_3 are obtained. These output components generated are independent of each other. ICA pictorial model is shown in Fig. 2, where $x_{i,j,H}$, $x_{i,j,S}$, $x_{i,j,V}$ are hue, saturation and intensity values corresponding to pixel at location (i, j) of the image in HSV plane. $s_{i,j,1}$, $s_{i,j,2}$, $s_{i,j,3}$are the independent components values obtained corresponding to the same pixel. By fixing randomly generated matrix in fast ICA, first independent component, S_1 contains mostly buildings and similar objects, second S_2 contains primarily shadows and other small objects, the last S_3 contains man made objects having low contrast or low intensity values as shown in Fig. 3b, 3c and 3d.

Interestingly, as seen from the left bottom corner of the image I_1, all ICA components do not detect vegetation cover, thus helping in separating man-made objects in the image.

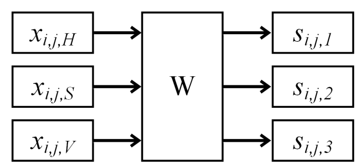


Fig. 2: ICA linear synthesis model

3.3. Post-Processing

The component containing maximum building areas, S_1 is used further for building detection. Otsu thresholding followed by morphological processing and geometric filtering is used to obtain final results.

3.3.1. Thresholding

Thresholding is aimed at segmenting out the region of interest. Otsu thresholding is a global thresholding technique which assumes two classes of pixels following bi-modal histogram of foreground and background. The threshold value is evaluated to minimize the intra-class variance. Otsu thresholding is applied to ICA output component S_1.

3.3.2. Morphological Corrections

Additional processing is done by applying morphological operations, opening followed by closing to remove noise from the image and smoothen the edges of regions. Opening is erosion followed by dilation, applied to remove unnecessary small objects in the image. Closing is used to fill small holes in the region.

3.3.3. *Geometric Filtering*

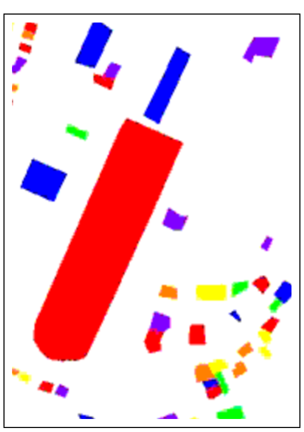
Minimum area of building was set to be $9m^2$. Any object having area less than that is not considered as a building. This filtering is applied to remove noisy edge pixels and other artifacts in the component images.

(a) Pan sharpened image I_1 (512x360)

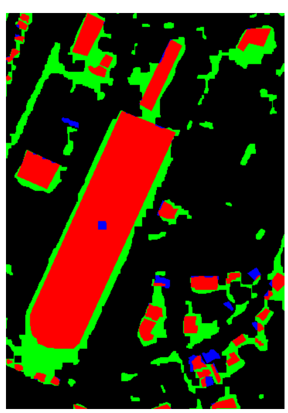
(b) ICA plane (S_1) of I_1

(c) ICA plane (S_2) of I_1

(d) ICA plane (S_3) of I_1



(e) Ground truth of I_1



(f) Image showing output results as Red:TP, Blue:FN, Green:FP

Fig. 3: ICA based building detection of image I_1

4. RESULTS

The dataset used is a diverse collection of both man made and natural objects and building characteristics ensuring very generic test case to evaluate the performance and robustness of the algorithm. The building characteristics and presence of other objects do not affect the performance of the algorithm except for extremely poorly illuminated buildings. An image containing manually annotated buildings was created to be used as the ground truth image. The performance of the building detection algorithm was evaluated at both pixel-level and object-level.

4.1. Pixel-level Performance Evaluation

The performance parameters for pixel-level evaluation are specified as follows:

- True Positive (TP) : The number of pixels correctly classified into building class by the algorithm.
- False Positive (FP) : The number of pixels incorrectly classified into building class by the algorithm.
- False Negative (FN) : The number of pixels incorrectly classified into non-building class by the algorithm.

$$Detection\ Percentage = \frac{TP}{TP + FN} \tag{3}$$

$$Branch\ Factor = \frac{FP}{TP + FP} \tag{4}$$

Table 1: Pixel level performance evaluation

Input Image	Performance parameters				
	TP	FP	FN	DP %	BF %
I_1	33647	25241	1506	95.72	42.87
I_2	48769	22942	10369	82.47	32
I_3	29025	19118	9742	74.87	39.71
Average				84.35	38.19

4.2. Object-level Performance Evaluation

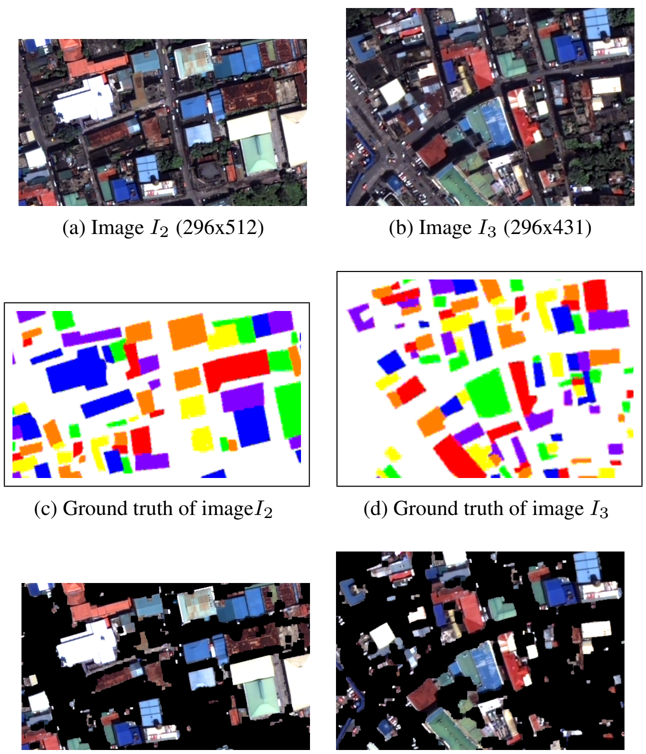
As our goal is building detection, object level performance analysis is carried out to understand whether the size and shape of the buildings have a role in the performance of the algorithm. The geometrical area of every extracted building is compared with the ground truth image. The building is considered as detected if more than 50% building area is detected by the algorithm, partially detected if 1% - 50% area is detected and undetected if no building pixel is detected by the algorithm.

The best performance of the algorithm was found for buildings having higher intensity values in the HSV plane.

The algorithm performance was not as good for very low intensity buildings.

Table 2: Object level performance evaluation

Input Image	Coverage parameters (No of buildings ÷ Total buildings)			
	Fully detected (%)	Partially detected (%)	Undetected (%)	Total buildings
I_1	85.37	7.32	7.32	41
I_2	67.70	20	12.31	65
I_3	64.37	17.24	18.39	87
Average	72.48	14.85	12.67	



(a) Image I_2 (296x512) (b) Image I_3 (296x431)

(c) Ground truth of image I_2 (d) Ground truth of image I_3

(e) Output of Image I_2 (f) Output of Image I_3

Fig. 4: Output results of Algorithm

5. CONCLUSIONS

A fast ICA based unsupervised building detection technique has been proposed and evaluated using a single pan sharpened multispectral image. The technique uses only three multispectral bands and does not require near infra red band for building detection as NIR band gives information of mainly vegetation region. It does not use any constrained models for building detection and can be applied to any general multispectral image. It is fairly robust as compared to previous work in detecting buildings varying in shape, size, color, height, orientation and pattern even in presence of vegetation, roads and shadows. The ICA decomposition of HSV plane of the image is a function of pixel intensity value and performs best when the value is high. The performance in case of very low intensity buildings may be improved by representing the image in a new color space before decomposition. Texture based features of the image can be utilized for further improving the performance.

6. ACKNOWLEDGMENT

The satellite image used in this experiment is taken from [3].

7. REFERENCES

[1] Lingjun Zhao, Xiaoguang Zhou, and Gangyao Kuang, “Building detection from urban sar image using building characteristics and contextual information,” *EURASIP Journal on Advances in Signal Processing*, vol. 2013, no. 1, 2013.

[2] Franz Rottensteiner and Christian Briese, “A new method for building extraction in urban areas from high-resolution lidar data,” *International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences*, vol. 34, no. 3/A, pp. 295–301, 2002.

[3] Bahadir Ozdemir, Selim Aksoy, Sandra Eckert, Martino Pesaresi, and Daniele Ehrlich, “Performance measures for object detection evaluation,” *Pattern Recognition Letters*, vol. 31, no. 10, pp. 1128 – 1137, 2010.

[4] Xiaoying Jin and Curt H Davis, “Automated building extraction from high-resolution satellite imagery in urban areas using structural, contextual, and spectral information,” *EURASIP Journal on Applied Signal Processing*, vol. 2005, pp. 2196–2206, 2005.

[5] Sönke Müller and Daniel Wilhelm Zaum, “Robust building detection in aerial images,” *International Archives of Photogrammetry and Remote Sensing*, vol. 36, no. B2/W24, pp. 143–148, 2005.

[6] A. Hyvarinen and E. Oja, “Independent component analysis: algorithms and applications,” *Neural Networks*, vol. 13, no. 4-5, pp. 411 – 430, 2000.

[7] Marian Stewart Bartlett and Terrence J Sejnowski, “Viewpoint invariant face recognition using independent component analysis and attractor networks,” *Advances in neural information processing systems*, pp. 817–823, 1997.

[8] Christopher J James and Christian W Hesse, “Independent component analysis for biomedical signals,” *Physiological measurement*, vol. 26, no. 1, pp. R15, 2005.