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Research Article

Building Change Detection in Myanmar using Image Processing

Ei Phyu Sin Win

Department of Information Technology Engineering, Technological University (Kyaukse), Upper Myanmar

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**Corresponding author:*
E-mail:
panthakhin9001@gmail.com

ABSTRACT

Building change detection makes it is easy to locate buildings from a distance in the sky. They can also observe the development of rural, or urban areas between 10 decade and present. So, higher resolution satellite and aerial pictures are needed to detect buildings. Building shape varies from one to another over the world. Rural areas are sparsely populated, but densely and complexly populated in urban areas. And it is difficult to detect separate buildings from them. To solve obstacles, non-linear filter, line extracting and region thresholding method is used in this research. The test images from the last decade and images of current year are acquired by using google earth pro, and have different spatial resolutions. Detection area is Hlaingthaya Township, Yangon, Myanmar. This system is simulated with MATLAB programming language.

Keywords: Building change, Last decade, Resolution, Detection

Introduction

Google Earth Pro Map provides satellite imagery of 2D and 3D buildings. The user can fly anywhere on the planet, from the galaxies of space to the bottom of the ocean. Guide the wealth of geography. The users can save her trip and share it with others. It gives very high-resolution image to provide valuable information. Particularly detection of buildings that come from these pictures need special attention. This is because of the information can be used in some remotes sensing applications such as automatic mapping, city planning and land use analysis. Apartments may be captured from different viewpoints, and may not have a unique representation.

Then they may have complicated fundamental interaction with the environment (such as shadow). Lighting and contrasting image may not be adequate to reliably find the building. Next these images can cover many geographic areas. It may take some time to analyze the image. Finally, the building does not have a standardized size and shape. Hence, Improvement of strongly and fast building detection algorithms aerial and VHR satellite images are now needed. Over the past 10 years, researchers have done just that method of building

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detection uses antenna and satellite statue. There are good reviews for detecting buildings in the antenna and satellite images.

FAST Local Feature extraction is used to extract feature such as building, ground, road and shadow. Therefore, it picks each extraction corner pixel as a local feature vector (LFV) coordination. Region masking algorithm is used to detect corner of ROI. The result of region masking is refining probably.

Literature Review

The researchers (Segl and Kaufmann, 2001) described the combination algorithm of supervised shape classification with unsupervised image segmentation. Their methodology provides seeking tiny things as buildings in higher resolution satellite pictures.

The research worker (Molinier *et al.*, 2007) pointed out finding margins of manmade structures in satellite images by training a self-organizing map.

The research author (Gamba *et al.*, 2007) utilized boundary data to obtain the map of an urban area. They pointed out two different classifiers such as boundary and non-boundary data. Then, they mixed the effects to detect urbanization area houses on very high-resolution images.

In these surveys, there is certainly a necessity for a training dataset.

The researcher (Benediktsson *et al.*, 2003) applied arithmetic morphological functions to pull out functional data to discover the area in satellite images.

Design and Methodology

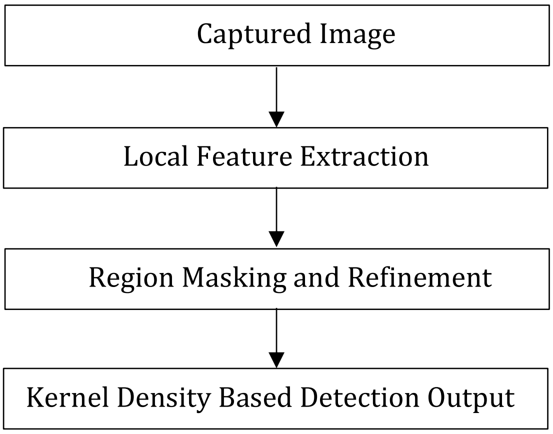


Figure 1. Proposed System Design

Data Description

The data point usage for this survey is a Google earth pro data, acquired near Hlaingthaya township in Yangon, Lower Myanmar. This system has in total, five datasets of the same area, most of which are satellite images. All the pictures in the time-series are east using many correlate points (Feb, 2003), enhanced by least squares point matching to achieve geographic information system with sub-pixel measurements (1116 x 632) pixels.

Table 1. Data Description

No.	Source	Captured Date	Pixel
1	Google Earth Pro (NASA)	2-2-2003	1116 x 632
2	Google Earth Pro (NASA)	23-2-2007	1116 x 632
3	Google Earth Pro (NASA)	19-1-2012	1116 x 632
4	Google Earth Pro (NASA)	29-1-2017	1116 x 632
5	Google Earth Pro (NASA)	8-4-2020	1116 x 632

These five data sets are acquired at various seasons of the year. Here, differences in lighting and changes in seasons are the main problems in analyzing time series changes.

Captured NASA Image

This system uses Maxar Technologies NASA Image.

Figure 2. Image captured Hlaingthaya Township Yangon at 2-2-2003 16⍰52' 56.55"N ,96⍰03' 18.16" elev27ft eye alt 1922ft

Local Feature Extraction

M. Fonte, S. Gautama.*2005* thought the better Harris and Susan corners detectors to get the type of structure in a planet picture.

They decided that the point sensor was not enough. Lonely to provide unique information about the type of structure from the picture. C. Schmid, (2000) on the other hand, the analysis of the system users compared different point detectors for each overall picture in application procedure. They have the best results provided by Harris Corner Detector C. Harris and M. Stephens, (1988). Therefore, the researcher selects firstly to retrieve the LFV. Harris and Stephens referred to point sensors in general Three stages known as Harris corner detector: Gradient the calculation forms a matrix and calculates the eigenvalue. First, they need to calculate the smoothen (using the Gaussian function). Tilt the x and y directions to see a given angle Scale image I (x, y). The smooth gradient filters for the x and y directions as the following;

$$g_x(x,y) = \frac{-x}{2\pi\tau_g^4} \exp\left(-\frac{x^2+y^2}{2\tau_g^2}\right) \qquad (1)$$

$$g_y(x,y) = \frac{-x}{2\pi\tau_g^4} \exp\left(-\frac{x^2+y^2}{2\tau_g^2}\right) \qquad (2)$$

Where τ_g is the smoothing parameter. The system regards this as unity. Paper and aerial imagery based on the size of NASA images. Then this method is quite strong for this variable, but it must be adapted according to the resolution of the pictures being examined. Next researcher calculates the smooth slope of the image or picture P (x, y) as

$$P_x = g_x (x,y) \times P (x,y) \qquad (3)$$

$$P_y = g_y (x,y) \times P (x,y) \qquad (4)$$

where × stands for 2D convolution operation and P(x,y) lets a picture or image. The Harris corner relys on estimating a matrix as the following;

$$T(x,y) = \begin{pmatrix} t_{xx} & t_{xy} \\ t_{yx} & t_{yy} \end{pmatrix} \qquad (5)$$

Where t_{xx}, t_{xy} and t_{yy} are the gradient magnitudes averaged over window D. Harris and Stephens recommended that exact eigenvalue calculation can be escaped by the following equation;

$$R(A) = |A| - K\ \text{trace}^2 (A) \qquad (6)$$

where K is a adaptive variable, ranged from 0.04 to 0.15. Harris corner-based LFV as K is the total number of detected Harris feature. The gradient orientation [O(x,y)] and magnitude[M(x,y)] for each picture coordinate as the following equation ;

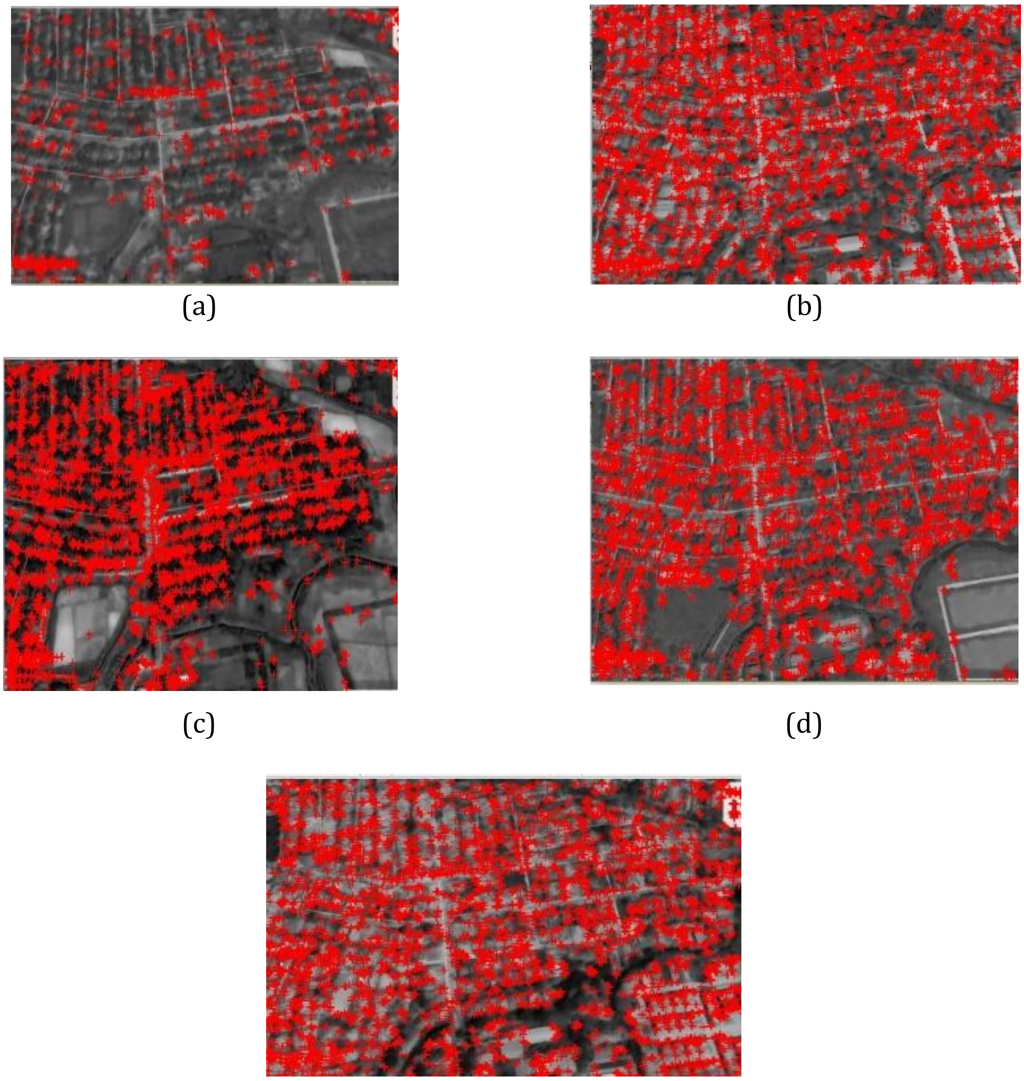
$$O(x,y) = \arctan\left(\frac{I_y(x,y)}{I_x(x,y)}\right) \quad (7)$$

$$M(x,y) = \sqrt{I^2}\,(x,y) + I^2\,(x,y) \quad (8)$$

The corner point at coordinate (x_i,y_i), the corresponding position is $\emptyset\, j = O(x_i,y_j)$.

Local Feature Vector using FAST

The system finally uses FAST method to extract local feature vector. E. Rosten, R. Porter, and T. Drummond recommended (2010) a FAST detection method. Image angle for a quick and reliable method Depends on detection angle, wedge pattern and machine Learning Techniques. That methodology can be easily informed as follows. Below are 16 candidate pixels for adjacent corners. the users checked if there was a series of consecutive pixels Candidate pixel tests are shown as angles. These experiments are made using machine learning techniques to accelerate things up, see for more information on how to do this.



(a) (b) (c) (d) (e)

Figure 3. Feature extraction of Test Hlaingthaya Township (Different Time) with the same coordination(K)

Region Mask

Masking is a certain method of image processing. Small "image fragments" and used to edit large images. Masking is a process in various types of image processing such as edge detection, motion detection and noise reduction. Regions of Interest (ROI) are the parts of the image that are filtered or perform other operations. To determine the ROI, create a binary mask. This is a binary image that is the same size as the image you are processing, using pixels whose ROI is set to 1 and all other pixels set to 0. The mask is a binary image. Contains zero and non-zero values. If a mask is applied to another binary or gray image of the same size, all zero pixels in the mask will be set to zero on the exported image. Everything remains unchanged.

Figure 4. Region Masking of Hlaingthaya Township in Yangon

Probability Refinement of Test Image

Build Probability Map (BPM) Training example defined as the measure of each pixel belonging to a daily BPM build class that may be inconsistent due to factors such as errors and errors. Omission of heavy snowfall classification by very similar spectral data of the following classes Therefore, we optimized the consistency of all BPMs using both weighting methods, taking into account the smoothness of the spatial boundary and the discontinuity in the height of the transient region

$$P_f(x,y,t)=\frac{1}{\sum w(x,y,t)}\sum m\sum n\sum_{k=1}^{h} w(m,n,k)P(m,n,t) \quad \ldots(9)$$

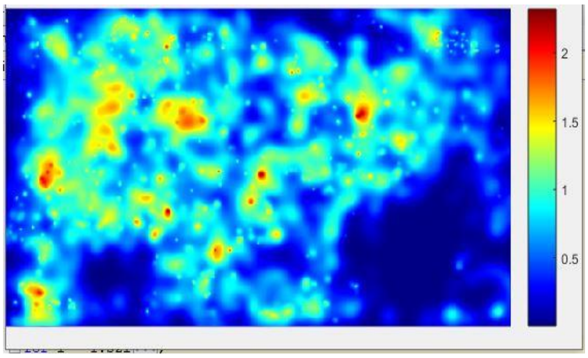


Figure 5. Refinement of Test Image

Kernel-Based Building Detection

Although, local feature vector indicates a building to be detected in the image, our method in detail, the system users start with kernel-based density estimation. Because of the users do not know the total number of buildings This test image uses a variable density based on the nucleus. Method of assessing their detection. As mentioned earlier use regional character vectors ($\vec{k}_h$, $\vec{k}_g$,$\vec{k}_f$ and $\vec{k}_s$) as observations. Without losing the generality Estimation of vector of general local properties k = (x_i, y_i, θ_i, w_i) When I = 1: .. .., Ki. This vector gives information about the building. It will be revealed.

Each local feature vector will have its effect as $\hat{x}i = xi + 0.5wi \sin(\theta i)$ and $\hat{y}i = yi + 0.5wi \cos(\theta i)$.

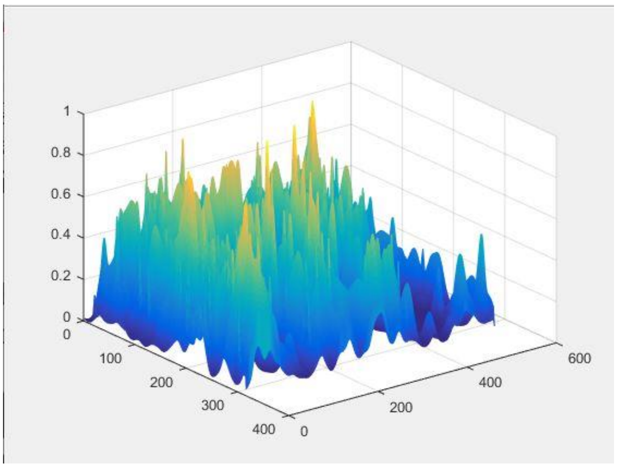


Figure 6 Hlaingtharya Township Test image kernel density approximation effects for four LFV extraction methods. ($\vec{k}_h$, $\vec{k}_g$,$\vec{k}_f$and $\vec{k}_s$)

For dark buildings, there are several local features based on Harris Corner. The vectors are oriented towards the center of the building. But Local vector of features based on family filtering, the feature vector is directed towards the center of the building.

Experimental Results

In this section, the system user tests building change detection and uses the old time NASA Images shown Table 1 above section. The system data set exists of color NASA pictures and aerial image sets with 1116*632 spatial resolutions, individually.

This two image sets are naturally gained by different sensors. Moreover, both aerial and NASA satellite test images are particularly picked up to represent wide and diversity of apartment aspects. Hence, they will offer trusty data on the achievements of this research technique.

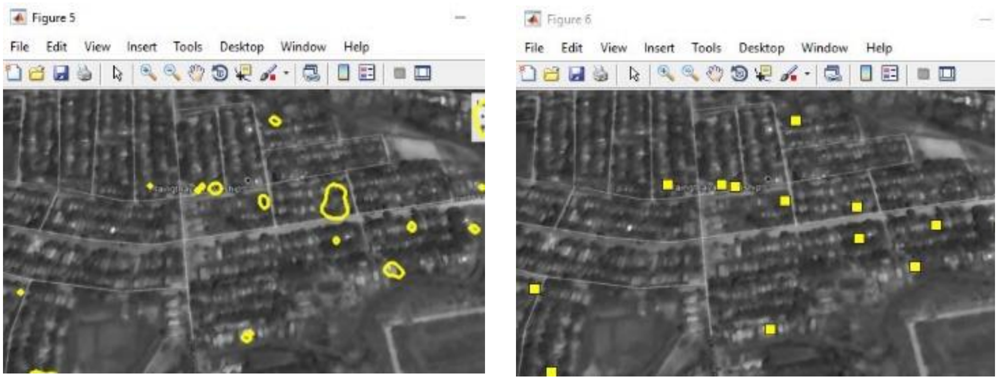


Figure 8. Detection Results of Hlaingthaya Township Captured at (2-2-2003)

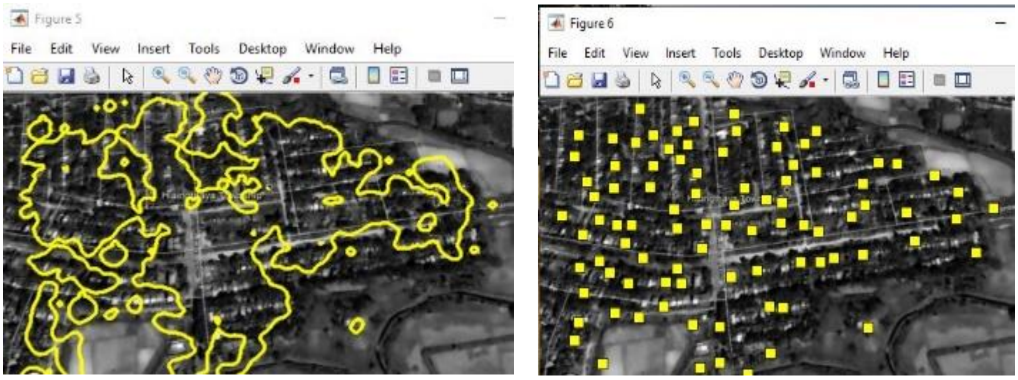


Figure 9. Detection Results of Hlaingthaya Township Captured at (23-2-2007)

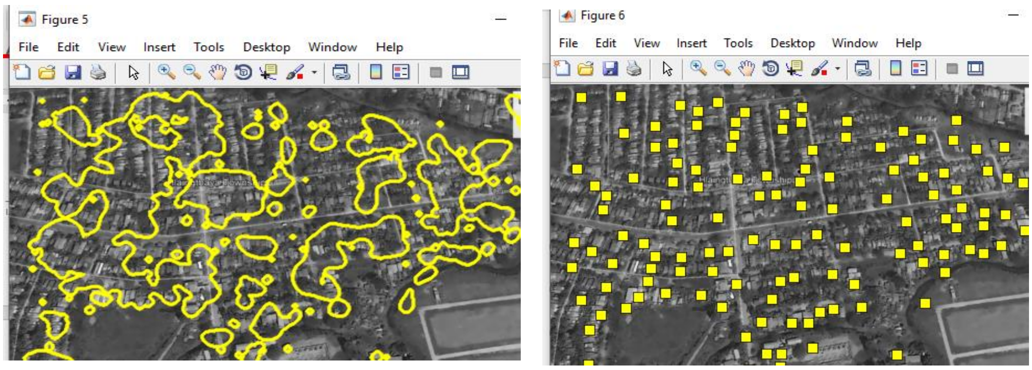


Figure 10. Detection Results of Hlaingthaya Township Captured at (19-1-2012)

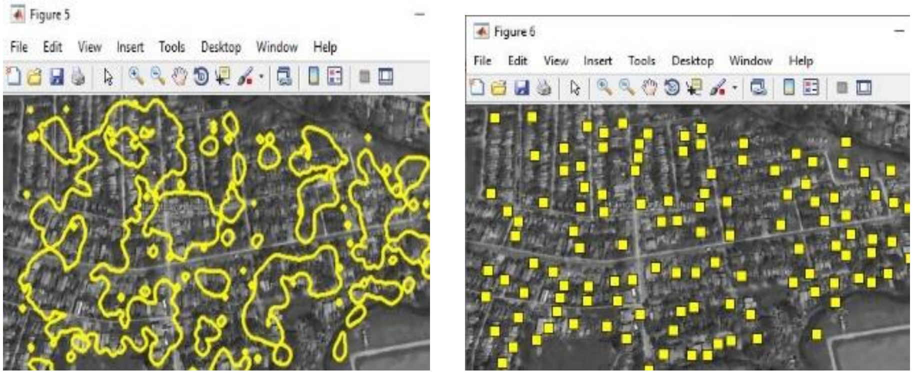


Figure 11. Detection Results of Hlaingthaya Township Captured at (29-1-2017)

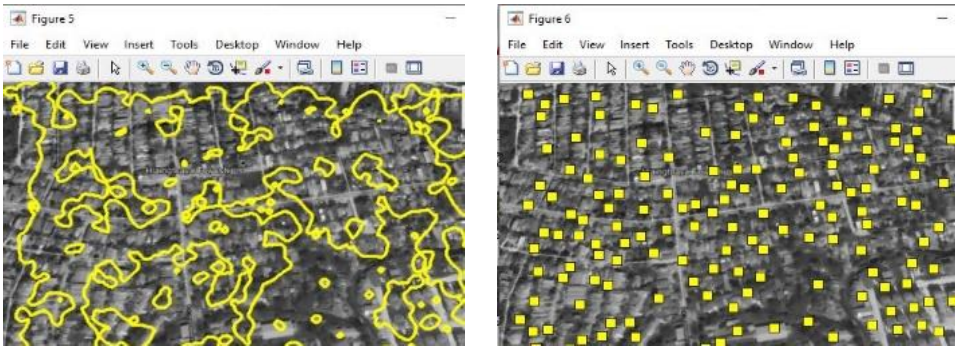


Figure 12. Detection Results of Hlaingthaya Township Captured at (8-4-2020)

Computation Time

Computation time of this system is very short. consider the time needed by all building detection modules in particularly relies on the experiment pictures.

Table 2. Computation Time to detect Buildings

Module	FAST
Preprocessing	10.7188
Local Feature Vector	7.5469
kernel Density	30.8125
Building Detection	0.3750
Total	49.4531

This system describes table with all CPU timings for each module in Table 2. In reporting these results, the system user used a PC with Intel Core i3 processor with 3-GHz clock speed and has 8 GB of RAM. The users used MATLAB 2016a as coding platform. Region thresholding is 1.5.

Conclusion and Discussion

Automatic building change detection for NASA image is researched in this journal from the last decades until present time. This research can help the users to understand how a city can improve and how it can improve its standard of living in a short period. This paper should consider region threshold, local feature vector values ($\vec{k}$) and without shadow. After a thorough test this method can detect most buildings (other Properly, both size, shape and strength) aeronautical satellite images and economy real time processing for further researches.

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References

K. Segl and H. Kaufmann, "Detection of small objects from highresolution panchromatic satellite imagery based on supervised image segmentation," *IEEE*

Trans. Geosci. Remote Sens., vol. 39, no. 9, pp. 2080–2083, Sep. 2001. https://ieeexplore.ieee.org/document/951105

M. Molinier, J. Laaksonen, and T. Hame, "Detecting man-made structures and changes in satellite imagery with a content-based information retrieval system built on self-organizing maps," *IEEE Trans. Geosci. Remote Sens.*,vol. 45, no. 4, pp. 861–874, Apr. 2007. https://cris.vtt.fi/en/publications/detecting-man-made-structures-and-changes-in-satellite-imagery-wi

P. Gamba, F. D. Acqua, G. Lisini, and G. Trianni, "Improved VHR urban area mapping exploiting object boundaries," *IEEE Trans. Geosci. Remote Sens.*, vol. 45, no. 8, pp. 2676–2682, Aug. 2007. https://ieeexplore.ieee.org/document/5523977

J. A. Benediktsson, M. Pesaresi, and K. Arnason, "Classification and feature extraction for remote sensing images from urban areas based on morphological transformations," *IEEE Trans. Geosci. Remote Sens.*,vol. 41, no. 9, pp. 1940–1949, Sep. 2003. https://www.researchgate.net/publication/261241425_Hedges_detection_using_local_directional_features_and_support_vector_data_description

L. M. Fonte, S. Gautama,W. Philips, andW. Goeman, "Evaluating corner detectors for the extraction of manmade structures in urban areas," in *Proc. IEEE Int. Geosci. Remote Sens. Symp.*, 2005, pp. 237–240. https://biblio.ugent.be/publication/406046

E. Rosten, R. Porter, and T. Drummond, "Faster and better: A machine learning approach to corner detection," *IEEE Trans. Pattern Anal.Mach.Learn.*, vol. 32, no. 1, pp. 105–119, Nov. 2010. https://ieeexplore.ieee.org/document/4674368

C. Schmid, R. Mohr, and C. Bauckhage, "Evaluation of interest point detectors," *Int. J. Comput. Vis.*, vol. 37, no. 2, pp. 151–172, Jun. 2000. https://hal.inria.fr/inria-00548302/document

C. Harris and M. Stephens, "A combined corner and edge detector," in *Proc. 4th Alvey Vis. Conf.*, 1988, pp. 147–151. https://www.semanticscholar.org/paper/A-Combined-Corner-and Edge-Detector-Harris-Stephens/