Road Detection from Google Earth Images using Segment Tests

Mustafa Teke

***Abstract*—Detection of interest point such as roads and buildings has taken a lot of interest. Aerial imagery has also became common as Google Earth and GPS systems are commonly used. Detection of roads is still an unsolved problem. In this paper an approach is proposed based on segment tests of multiple detection methods.**

***Index Terms*—Road Detection, Segmentation, Satellite Imagery**

I. Introduction

Satellite imagery has been very important ever since first surveillance satellites were in service. Apart from surveillance of military targets, commercial use satellite imagery has become common especially after the introduction of Google Earth [1] and cheap GPS Navigation devices. Roads from those images extracted manually and expensive process. Obtaining roads from a foreign country is hard and much more expensive than obtaining national roads. Moreover roads might dynamically expand their size and extend to new places. For these reasons importance of automatic road extraction is obvious. However extracting roads from satellite imagery is no trivial task. Roads have no unique property and dependent on their use and location. Also, roads are not isolated from their surroundings, for example shadows from objects, Trees over around the roads and vehicles makes harder the detection of the roads.

II. Relevant Work

There are various methods to detect roads. Seed points are used in [2] for region growing of roads. Edge analysis is applied in [3]. In [4] road network detection is achieved by applying morphological operations. Edge detection based on road detection is used in [5]. In [6] deformable snake models are used for detection and localization of boundaries. Snake models are also utilized in [7] to detect roads in a semiautomatic manner. Dynamic programming with Markov dynamic chains of stochastic processes is used by [8]. In [9] segmentation based texture analysis is used to detect roads. Roads are detected at different scales by using multi-resolution analysis by using wavelet analysis in [10]. There are also stereoscopic and multi-temporal analyses based methods. GIS based methods are also used to detect roads [11].

M. T. Author is with the Graduate School of Informatics, Middle East Technical University; e-mail: Mustafa.teke@gmail.com).

III. Segment Tests

The Proposed method is based on ensemble of weak learners from machine learning [12]. Consensus of weak learners is used to determine the decision. Boosting and Bagging are common weak classifier based methods [13]. Bagging replicates training sets by sampling with replacement from the training instances. Boosting uses all instances but weights them and therefore produces different classifiers.

Various properties of roads are investigated. Using the exploited features 6 road detectors developed. These detectors operate on segments which have been determined by Mean-shift Segmentation [14]. Figure 2 shows the segmentation result of Figure 1.

Figure 1 A test image from urban area, image 40.

Figure 2 Segmentation results of Figure 1

The first detector based on the assumption that roads are large objects compared to other objects. This detector finds large segments. Edges of images are found by Canny edge detector [15]. Canny edge detector is an optimal edge detector with low error rate. Segments with high density of edges are selected as road candidates in the second detector. Color properties of roads are common, color of asphalt, gray color. Roads have low Hue and small variance between their RGB color components, i.e. on the main diagonal of the RGB cube. The third classifier controls the hue of segments. Segments with low hue are labeled as road candidates. Similarly segments with lower variance in color are labeled as roads in the fourth classifier. Roads are large objects and as a result they have been observed to large number of interest points. Interest points in the image have been extracted by using FAST [16] corner detector. Segments with higher average number of interest points per segment selected as possible roads by the fifth detector. A final test has been applied by checking average radius skeletons of the segments. Segment which have average width between 6 to 25 meters are selected as road candidates by the sixth detector. Diagram of detectors are shown by Figure 3.

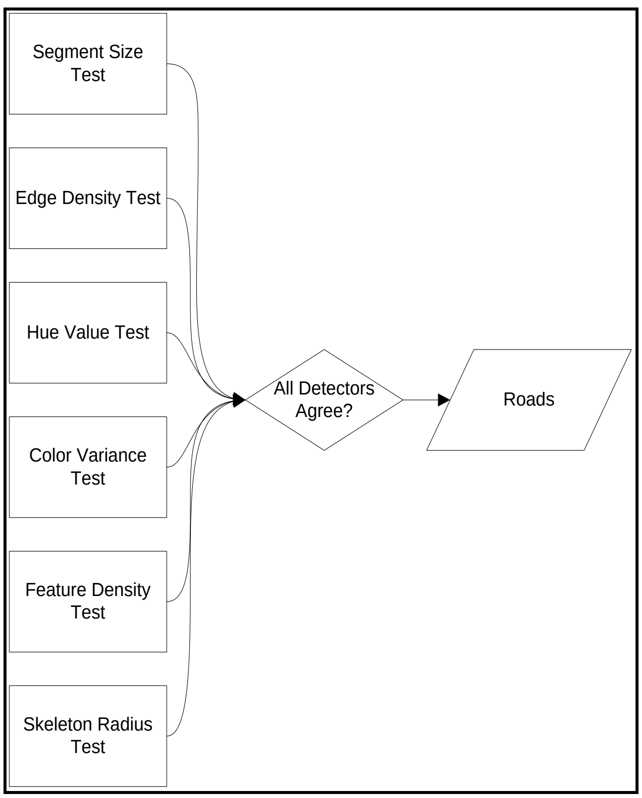


Figure 3 Ensemble of Detectors

Figure 4 Results of 1st Detector (Segment Size)

Figure 5 Results of Canny Edge Detector

Figure 6 Results 2nd Detector (Edge Density)

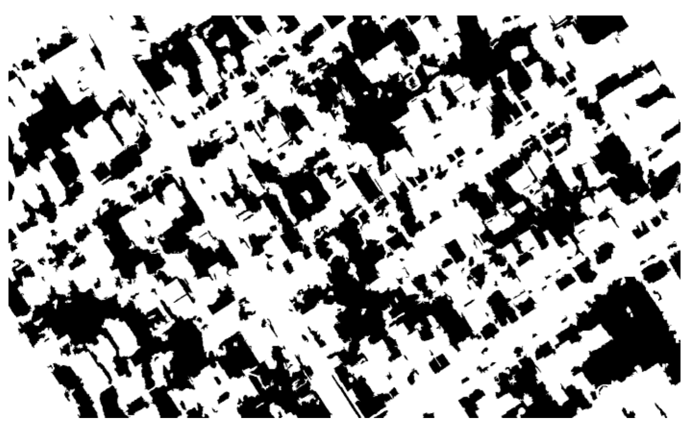


Figure 7 Results of the 3rd Detector(Hue Value)

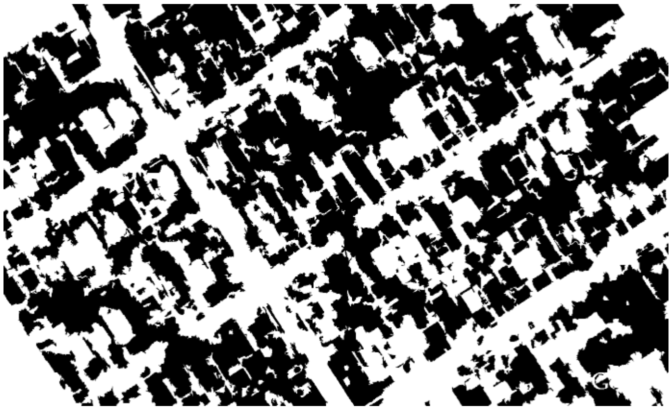


Figure 8 Results of the 4th Detector (Color Variance)

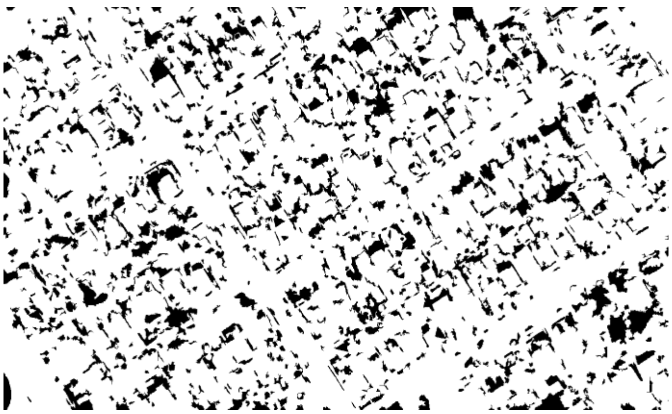


Figure 9 Results of the tth Detector (Feature Density)

Figure 10 Skeletons of the Segments

Figure 11 Results of the 6th Detector (Skeleton Radius)

These detectors are allowed to have large false alarm rate but high recall. They have parameters so that their miss rate is very low. False positives are reduced in the ensemble of these classifiers; for example water, red roofs and vegetation are removed.

Figure 12 Results of Ensemble of Classifiers

Results of the Hough transformation have been used to detect straight lines but due to occlusion roads in urban areas do not always have straight edges. Also long buildings appear to have straight edges.

Figure 13 Hough Lines of Figure 1

Assigning multiple detectors has a drawback when one of the detectors does not find objects correctly. This drawback is tried to overcome by giving high tolerance for individual detectors.

IV. Experimental Results

Experimental results for the test images are given in Table 1. Due to occlusions from objects on the roads detection performance degrades. Recall values are usually high; however precisions values indicate there are false alarms.

Table 1 Precision, Recall and F-Score for test images.

	Precision	***Recall***	***F***
original_image_7	0.61	0.77	0.68
original_image_26	0.27	0.74	0.39
original_image_40	0.63	0.57	0.60
original_image_41	0.78	0.65	0.71
original_image_42	0.43	0.69	0.53
original_image_43	0.42	0.59	0.49
original_image_77	0.29	0.21	0.24

False alarms are usually from the building as buildings with similar features as roads. Roads can be cleared using shadows as the buildings have little shadow with the exception of bridges. Also if we had access to 4-band imagery it would be possible to remove vegetation.

V. Conclusions and Future Work

Deploying ensemble of detectors which exploits individual properties of roads is an effective way of detecting objects however this method heavily dependent on performances of the detectors. Detection performance degrades greatly even on of the detectors fails to find objects. Assigning weights or voting can solve this problem. Some detectors produce more accurate results than others. In this case, redundant detectors could be removed. 3-band shadow detection algorithms could be used to remove buildings to remove false alarms from buildings as an improvement. Also existence of cars could be used to find roads in urban areas.

Appendix

Source code is available at:
http://mustafateke.com/projeler/road-detection/ .

Figure 14 Visual Results for Image 7

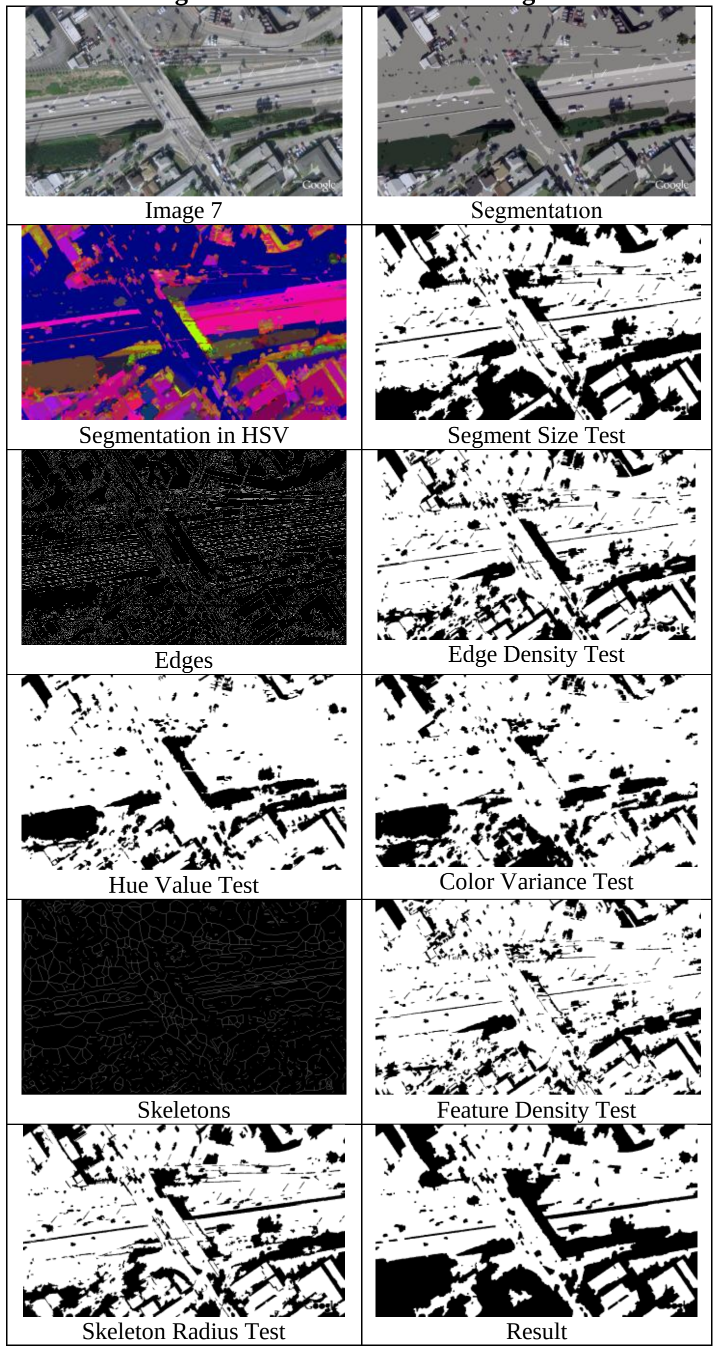


Figure 15 Visual Results for Image 26

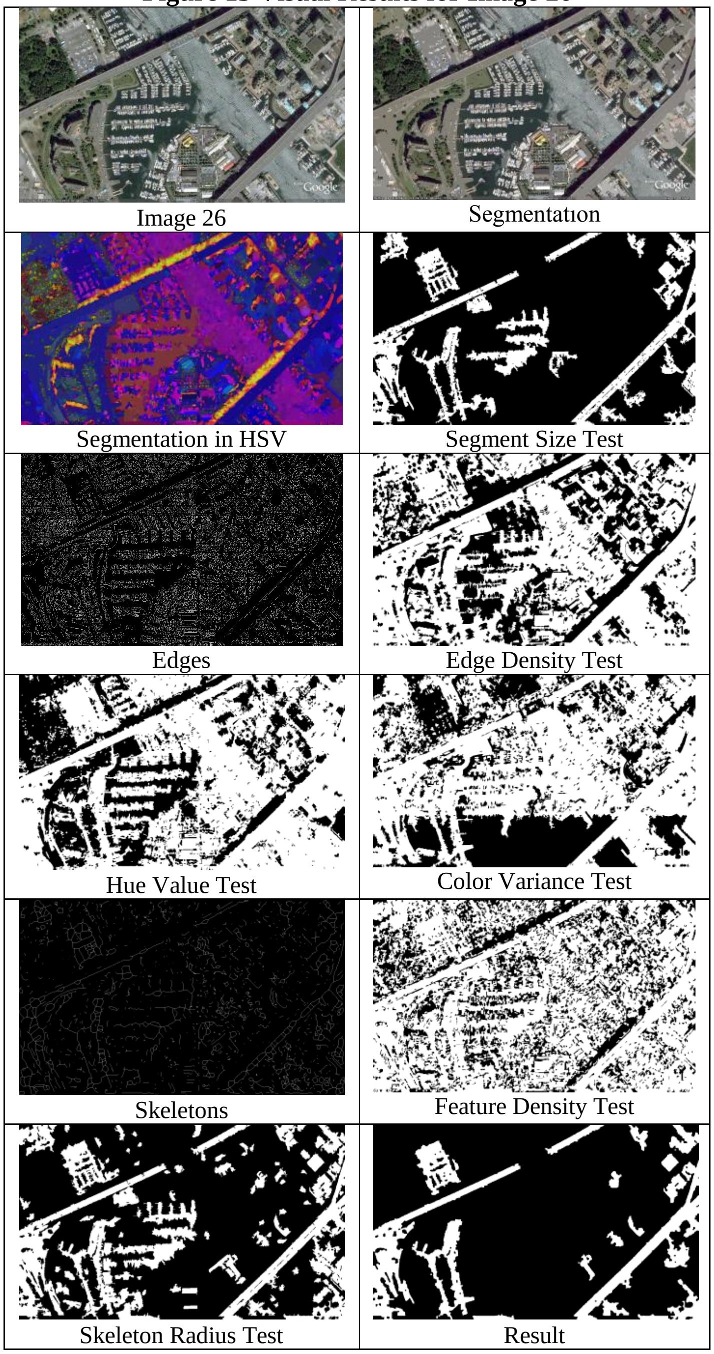


Figure 16 Visual Results for Image 41

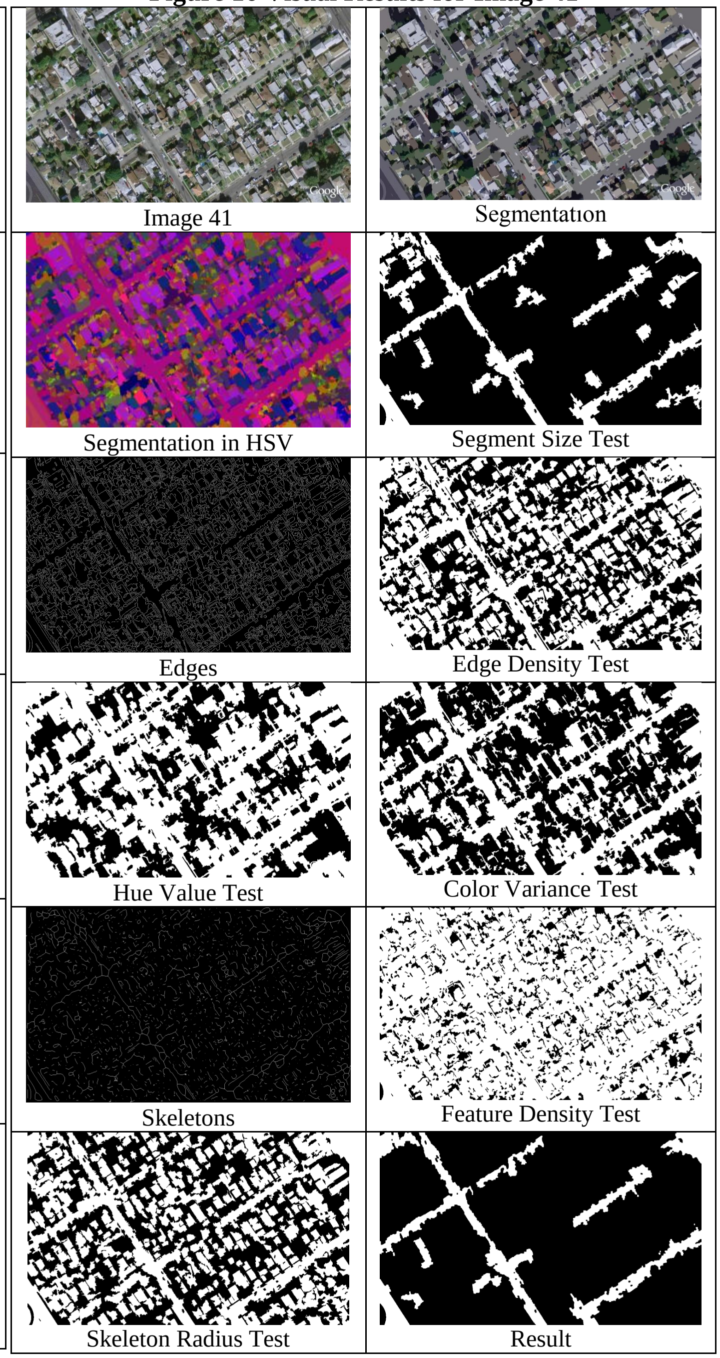


Figure 17 Visual Results for Image 42

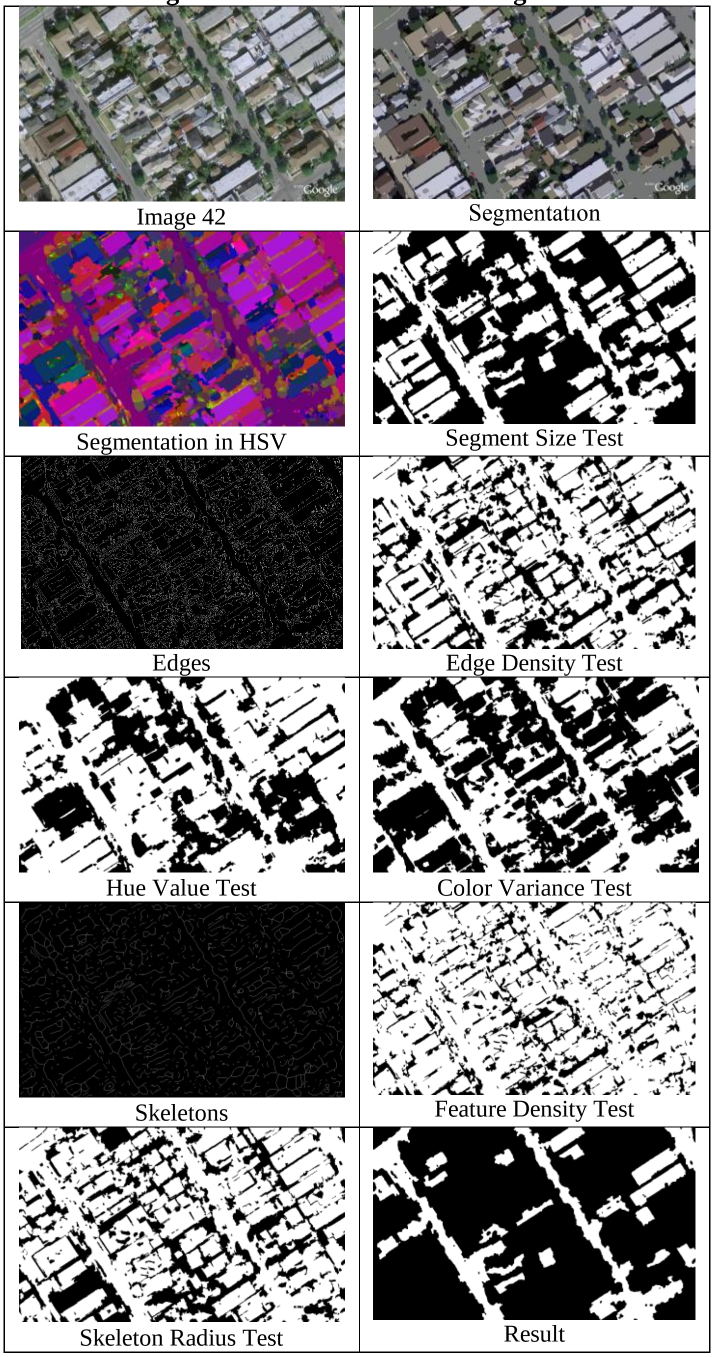


Figure 18 Visual Results for Image 43

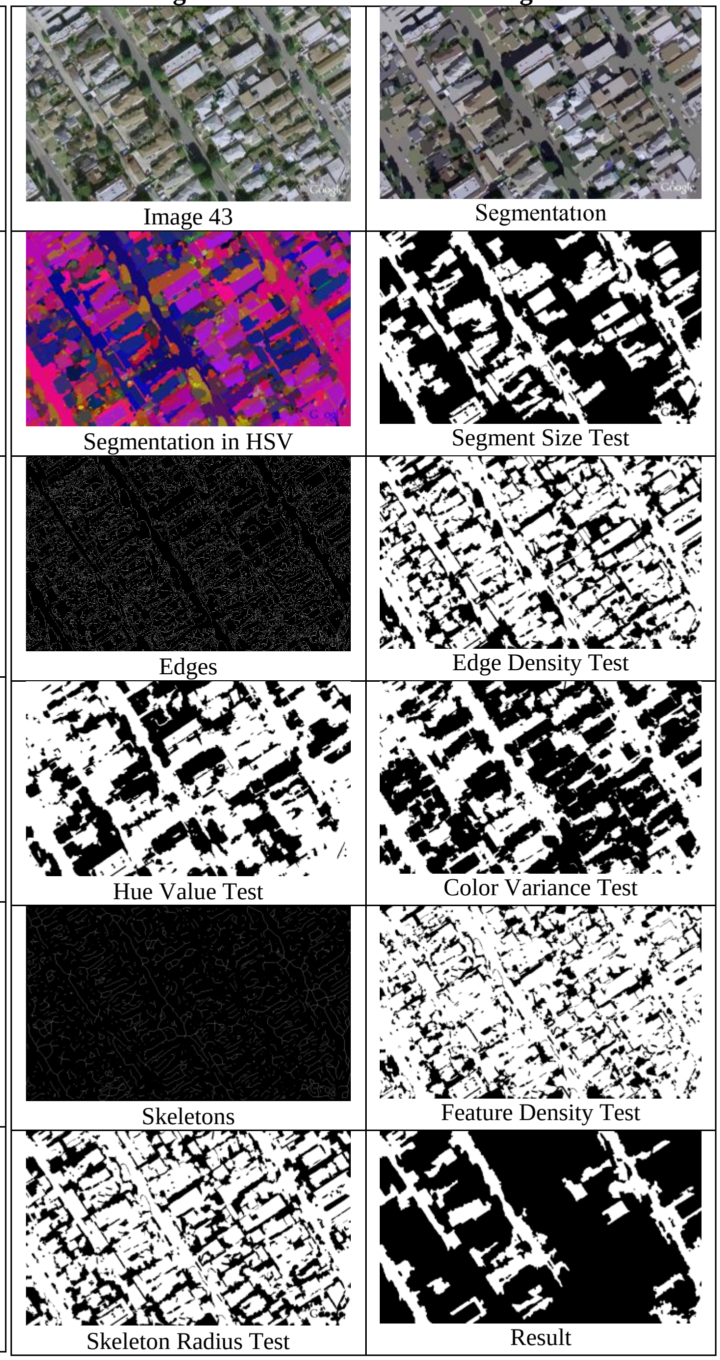
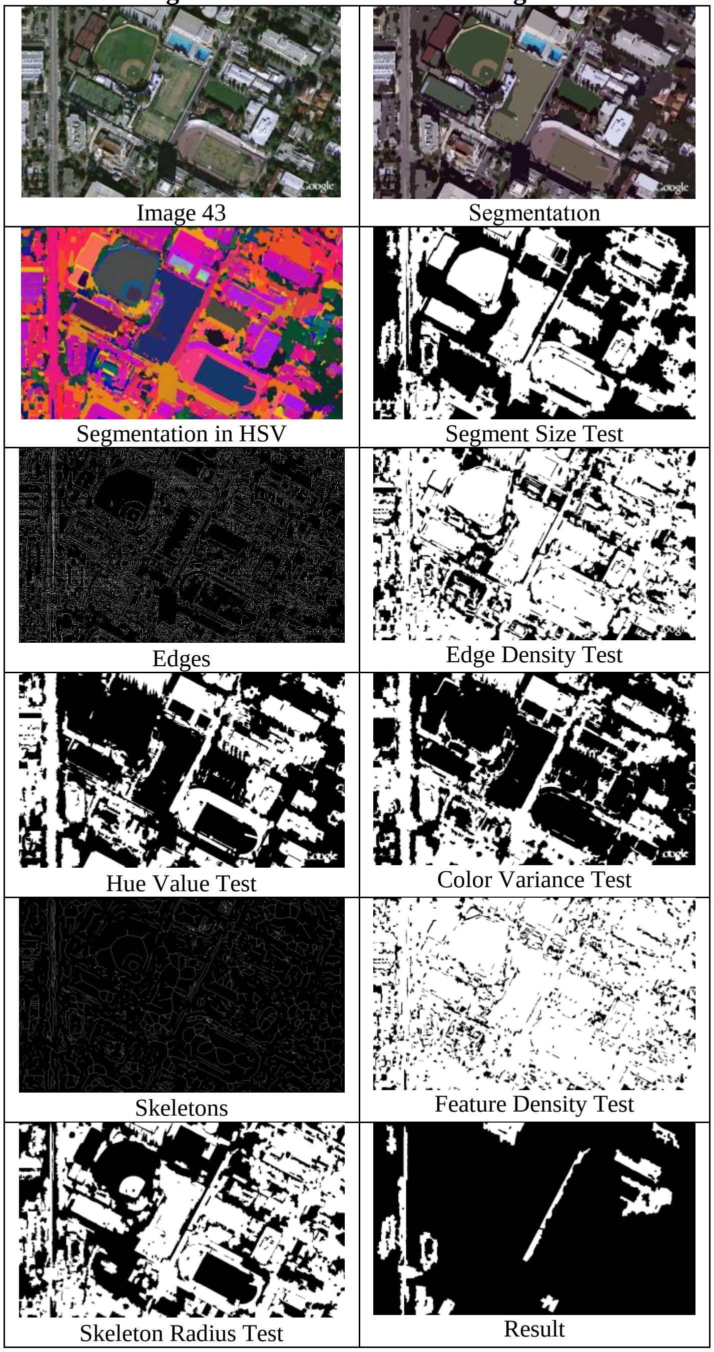


Figure 19 Visual Results for Image 77



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First A. Author (BS'05–MS'10–) graduated from Electrical and Electronics Engineering from Middle East Technical University in 2005 (BS) and graduated from Information Systems in 2010 (MS)

He is currently working as a software engineer.