

Road Region Extraction from RSI using K-Mean HFT Segmentation Technique

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Abstract

The extraction of roads from digital images is essential for automatic mapping, effective urban planning and updating of GIS databases. The very high spatial resolution images (VHR) taken by space and space probes are the main source of an accurate extraction of the route. The extraction of road networks in remote urban areas of images plays an important role in many urban applications (eg. Road traffic, geometric correction of remote sensing images in cities, updating geographical information, etc.). Because of the complex geometry of buildings and the geometry of sensor detection, it is generally difficult to distinguish the road from its background. In this research work the image segmentation techniques used for image remote sensing are discussed and evaluated. It has been found that there is no perfect method for image segmentation because the result of image segmentation depends on many factors, i.e. Pixel color, consistency, intensity, image similarity, image content and problem area. In this research work, a hybrid method is proposed for the extraction of paths from high resolution images based on the segmentation of the mean and HFT segmentation. The proposed method includes: noise suppression using the Lucy-Richardson algorithm, then a further improvement of the contrast between the initial segmentation of road and non-road pixels using the segmentation means k and finally HFT based segmentation. Simulation will be conducted on remote sensing images in urban, suburban and rural areas to demonstrate the proposed method and compare it with other similar approaches. The results show the validity and superior performance of the proposed extraction method.

Keywords – Remote Sensing Images, Road Extraction, Image Processing, Image Enhancement, K-Mean Segmentation, HFT Segmentation.

1. Introduction

Remote images consist of photos of the Earth or other planets made of remote satellites. Remote images have many uses in agriculture, geology, forestry, biodiversity conservation, land use planning, education, reconnaissance and war. Images can be in visible colors and other spectra. Remote sensing applications (RS) mainly include: urban remote sensing, basic geographic mapping, environmental monitoring and evaluation, precision agriculture and public information services, etc. [1]. The purpose of the RS applications is to obtain information and identify the objectives involved in order to complete the understanding of the image.

Some of the applications of remote sensing are such as: Road Detection, Building Detection, Land Surface Detection, Ship Target Detection.

Road extraction from a RS image is a challenging but important research topic. Roads are the backbone and essential modes of transportation, providing many various supports for human civilization. The analysis of road extraction is of great significance for traffic management, planning, road observation, GPS navigation and map change, etc [2].

To identify the streets of high-resolution remote sensing images and distinguish them from other objects such as buildings, rivers and forests, color information, which is usually in four or more spectral regions, can be used as an important feature. . The decision to choose one or the other depends on the balance between speed, accuracy

and complexity of the computer algorithm. Furthermore, this predicted accuracy may be related to the quality of the input data compared to the resolution of the digital image.

Satellite images can be viewed as raster images and digital raster images can be classified as representations of scenes with imperfect representations of objects. The imperfections of a picture derive from the imaging system, signal noise, region dispersion and shadow. Therefore, the task of identifying and extracting the specified data or characteristics of a halftone image is predicated on a criterion developed to determine a specific characteristic (based on its properties in an exceedingly halftone image), whereas the presence of alternative characteristics and imperfections of the raster image [3].

The difficulty in extracting the road from the RS images is that the image characteristics of road entities can be influenced by the type of sensor, the spectral and spatial resolution, the weather conditions, the variation of light and the ground conditions. In practice, a road network is too complex to be modeled with a general structural model. Therefore, the analysis of road characteristics and road models is very important [4]. This research is devoted to explore the automatic object extraction problem.

2. Related Work

Heermann and Khazenie et al. [1] proposed the back propagation (BP) algorithm, that permits the fast development of path extraction ways supported neuronal networks. Early work was chiefly supported the spectral and discourse information of the pixels within the image using the BP neural network and also the improved model to classify them directly.

Tu-Ko et al. [3] presented a solid approach to the demarcation of the road axis in which a network of neurons with spectral and on-board information was formed. Although extraction results include many off-road segments, the whole system can work well.

Mokhtarzade and Valadan-zoej [4] used a BP neural network method. By inserting various parameters, they were able to obtain the optimal input vector and test a variety of network structures with the iteration time. The optimal network structure and the termination condition of the converter can be determined under these conditions, but the process of input parameters is relatively heavy.

Yager and Sowmya [5] used the SVM classifier using edge-based features such as gradient, edge intensity, and edge length, but accuracy is relatively low, as many researchers have reported.

Melgani and Bruzzone [6] used SVM methods to classify a high resolution RS image. In many cases, the SVM classification methods are better in terms of precision, stability and robustness than those of the neural network with radial base function neural network and K-nearest neighbor classifier in terms of the accuracy, stability and robustness.

Tao and Jin [7] given a technique of partitioning the pixel as a segmentation criterion to tell apart objects from the background. The analysis uses the grey level coefficient matrix to explain the connection between the pixels. The system performance is excellent.

Liu and Wang [8] proposed an interactive method of image segmentation based on graph theory. You can quickly get the probabilistic model of the textures, colors and edges of the image.

Jianhua Wang et al. [9] proposed a knowledge-based roadside detection technique that consisted solely of high resolution post-disaster remote detection images. The central line of the road is extracted supporting the predetermined starting points of the road. Thus, characteristics such as road brightness, variance, angularity and proportions are called models of knowledge. Finally, under the direction of the central line of the road, the roads are extracted after the disaster, and therefore the damaged roads have been recognized by applying the model of knowledge.

The Mean-Shift method proposed by Comaniciu et al.[10] and the simple linear iterative clustering (SLIC) method proposed by Achanta et al.[11], both used the idea of clustering with different specific methods and advantages and disadvantages. The average offset method runs in iterative mode with a search process. Although it generates

super pixels of regular shape, it has the disadvantage of slow computation and lack of control over the number and size of super pixels.

3. Proposed Work

In this research work, the first problem is finding an unknown object of interest and the second one of detecting a known object of interest task-specific object detection or simply object detection. For the former, the proposed algorithm is developed to detect object from the remote images.

Figure 1 shows the proposed flow of algorithm. The proposed algorithm is designed for object detection from geo-satellite images.

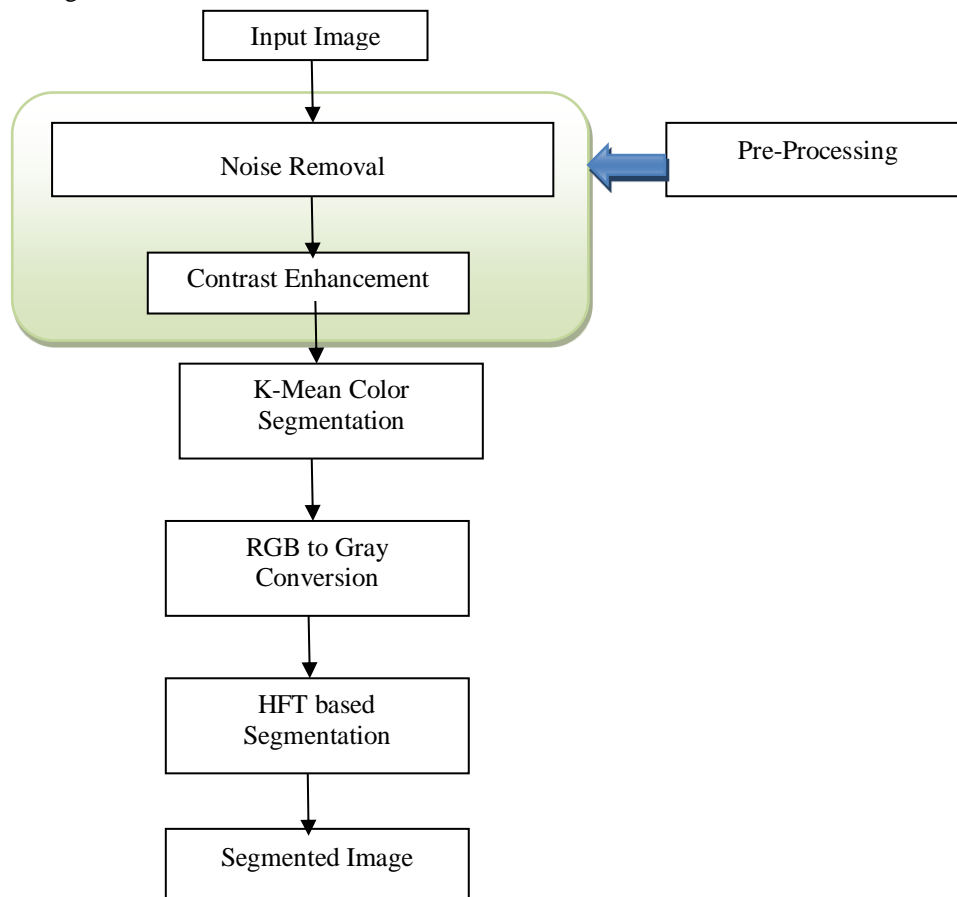


Figure 1: Proposed Algorithm

The proposed algorithm is described in steps as follows:

Procedure: Object detection from RSI

Input:

Geo satellite images

Output:

Object detection in images

Step 1: Take input image.

Step 2: Afterward enhance the given image using Lucy-Richardson Algorithm is used for noise removal. Lucy Richardson (LR) algorithm is an iterative nonlinear restoration technique.

Step 3: After noise removal contrast of the image is enhanced.

Step 4: Further applying k-mean color segmentation.

Step 5: Then color segmented image is converted into grayscale image.

Step 6: Compute the feature vector or maps.

Step 7: Form the hypercomplex matrix $f(n,m)$ by combining these feature maps

Step 8: Perform the Hypercomplex Fourier Transform on $f(n,m)$ and compute the amplitude spectrum A, phase spectrum, P and eigen axis spectrum.

Step 9: Smooth the amplitude spectrum with Gaussian kernels thereby obtaining a spectrum scale space.

Step 10: Final Segmented object S.

In this section, the proposed methodology discusses the object region of interest computation using only one feature map (that of intensity). However, in order to obtain better performance, more features are required, for example, color information. For such the proposed algorithm uses the so-called Hypercomplex matrix to combine multiple feature maps. Consequently, the Hypercomplex Fourier Transform (HFT) is employed to replace the Fourier Transform used for region of interest computing.

Before describing of proposed algorithm steps first of all there is description of about some concepts that is used in proposed algorithms.

K-Mean Segmentation

Image segmentation is one of the most commonly used methods for correctly classifying pixels in an image in a decision-oriented application. It divides an image into a number of discrete regions, so that the pixels in each region have a high similarity and high contrast between the regions. There are several techniques for image segmentation such as threshold, border, cluster and so on. One of the most efficient methods is the cluster method. One of the most commonly used clustering algorithms is k-means clustering. It's simple and faster than hierarchical clustering. And it can also work for many variables. But it generates a different cluster result for a different number of cluster numbers.

Grouping may be a technique of dividing a record into a particular variety of groups. this is often one among the foremost popular ways is K-Means clustering. In k-means clustering, it divides a set into a k-number data group. Classify a given set of information in k disjoint teams. The K-Means algorithm consists of 2 distinct phases. within the 1st phase it calculates the k-centroid and within the second phase it takes each purpose within the cluster with the centroid closest to the individual data point.

There are many ways to outline the distance of subsequent center of gravity and one among the foremost commonly used ways is Euclidian distance. Once the cluster is complete, calculate the new orientation of each cluster supported this new and a new euclidian focus distance between each center and every data point are calculated and also the cluster points that have a euclidian distance the minimum is assigned. Every cluster of the partition is defined by its member objects and its center of gravity. The goal of every cluster is that the point at which the sum of the distances of all objects in this cluster is decreased. K-Means is an iterative algorithm that minimizes the sum of the distances from every object to the cluster center of gravity in all clusters.

Consider an image with a resolution of $x \times y$ and the image must be grouped in the group number k. Let $p(x, y)$ be an input pixel to be a cluster and c_k cluster centers.

The algorithm for grouping k-means is as follows:

- Initialize number of cluster k and centre.
- For each pixel in an image, calculate the Euclidean distance d between the center and each pixel of an image using the relationship shown below

$$d = | p(x, y) - c_k | \quad (1)$$

- Assign all pixels to the nearest center based on distance d.
- After assigning all the pixels, recalculate the new central position using the following relation:

$$c_k = \frac{1}{k} \sum_{y \in c_k} \sum_{x \in c_k} p(x, y) \quad (2)$$

- Repeat the process until it reaches the tolerance or error value.
- Change the cluster pixels in the image.

Although k-means has the great advantage of being easy to implement, it has some drawbacks. The quality of the cluster final results depends on the arbitrary choice of the initial focus. Therefore, if the initial attention is chosen randomly, different results will be obtained for the different starting centers. Therefore, the initial center is carefully selected to obtain the desired segmentation. And computational complexity is another notion that we need to consider when we design the K-Means cluster. It is based on the number of data elements, the number of clusters and the number of iterations.

Hypercomplex Fourier Transform

The input to the traditional Discrete Fourier Transform is a real matrix. Each image pixel is an element of the input matrix and is a real number. However, if more than one feature is combined into a hypercomplex matrix, each element is a vector and this hypercomplex matrix is a vector field. Thus, the traditional Fourier Transform becomes unsuitable for computational purposes. The modified Hypercomplex Fourier Transform is proposed, in which the hypercomplex input was specified to be a quaternion⁵. Given a hypercomplex matrix:

$$f(n, m) = a + bi + cj + dk, \quad (3)$$

the discrete version of the HFT of is given by:

$$FH[u, v] = 1/\sqrt{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} e^{-\mu 2\pi i \left(\frac{mu}{M} + \frac{nv}{N} \right)} f(n, m) \quad (4)$$

where μ is a unit pure quaternion and $\mu^2 = -1$. Note that $FH[u, v]$ is also a hypercomplex matrix. The inverse Hypercomplex Fourier Transform is given as:

$$f(n, m) = 1/\sqrt{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} e^{-\mu 2\pi i \left(\frac{mu}{M} + \frac{nv}{N} \right)} FH[u, v] \quad (5)$$

Hypercomplex Representation of Multiple Feature Maps

The Hypercomplex representation can be employed to combine multiple features as color, intensity and motion as the features. We define the input hypercomplex matrix as follows:

$$f(n, m) = w_a f_a + w_b f_b i + w_c f_c j + w_d f_d k \quad (6)$$

where $w_a - w_d$ are weights and $f_a - f_d$ are the feature maps (matrices) and:

$$f_b = (r + g + b)/3,$$

$$f_c = R - G,$$

$$f_d = B - Y,$$

where r, g, b are the red, green and blue channels of an input color image and

$$R = r - (g + b)/2, \quad G = g - (r + b)/2 \quad (7)$$

$B = b - (r + g)/2, \quad Y = (r + g)/2 - |r - g|/2 - b$. These three feature maps comprise the opponent color space representation of the input image our approach has also been experimentally confirmed using videos by defining a motion feature M and setting $f_1 = M$. In this research work, we consider the static image case as well as motion case of videos by employing just intensity and color information. We select the weights so that $w_1 = 0.5, w_2 = 0.5, w_3 = w_4 = 0.3$

4. Implementation

In this research work a database is created using collection of different images from remote sensing images of size 512*512 pixels to show the performance of proposed algorithm. To evaluate the performance of the proposed system following parameters such as Accuracy, Precision/Correctness, Recall/Completeness and Fmeasure are used.

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

$$\text{Fmeasure} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

$$\text{Quality} = \text{TP} / (\text{TP} + \text{FP} + \text{FN})$$

Where, True Positive (TP) = Correctly detected object in image.


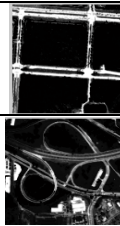

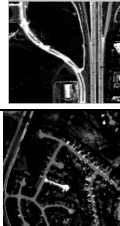

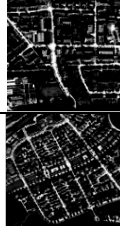

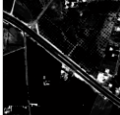


True Positive (TN) = No object region correctly detected in image.


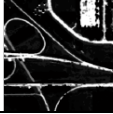

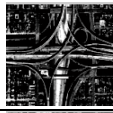


False Positive (FP) = Object incorrectly identified in images.

False Negatives (FN) = Object that are failed to be detected in image.

The results of proposed methodology are evaluated on 10 different input images the result analysis of these images is illustrated in Table I. To evaluate the performance of the saliency detection on the parameters such as Precision, Recall, Accuracy, Fmeasure and Time are compared are illustrated in figure 2-5.

Table I: Result Analysis of RSI Region of Interest

Input image	Segmented Image	Recall	Precision	Accuracy	F_measure
		1	0.9207	0.9707	0.9587
		0.907	0.9297	0.9158	0.9182
		1	0.9627	0.9828	0.981
		1	0.8666	0.9312	0.9285
		1	0.8723	0.9411	0.9318
		1	0.8548	0.9249	0.9217
		1	0.9055	0.9615	0.9217

		1	0.8595	0.937	0.9217
		1	0.907	0.9496	0.9217
		1	0.8844	0.9429	0.9217
AVERAGE		0.9907	0.8963	0.9457	0.9326

Comparative Analysis

Table II: Result Analysis of RSI Region of Interest

Algorithms	Recall	Precision	Accuracy	Quality
Proposed Method	99	89	95	88
Rasha Alshehhi [14]	93.4	90.9	-	85.4
Sujatha and Selvathi [12]	82.2	74.5	-	64.2
Maurya et al. [13]	84.6	82.0	-	71.3
Yue Li [15]	-	-	94	-
Hamid Reza [16]	-	-	81.8	-

Table II Shows the comparative analysis of different contributions or works that have been presented in road extraction from RSI. Four different parameters are used to compare the result analysis with proposed algorithm.

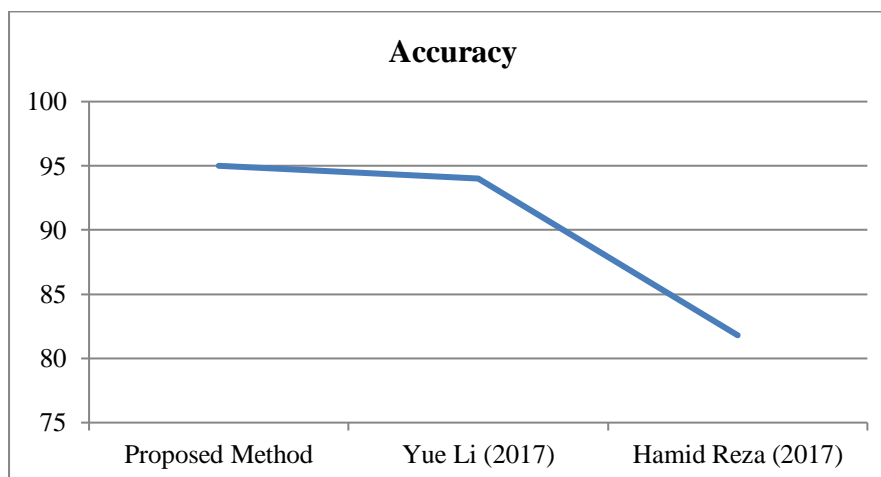


Figure 2: Comparative Analysis of Accuracy with Existing Work

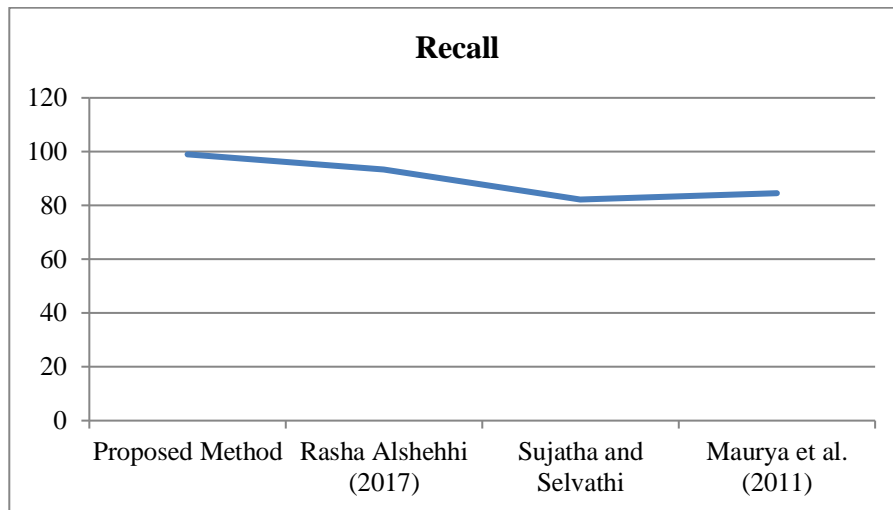


Figure 3: Comparative Analysis of Recall with Existing Work

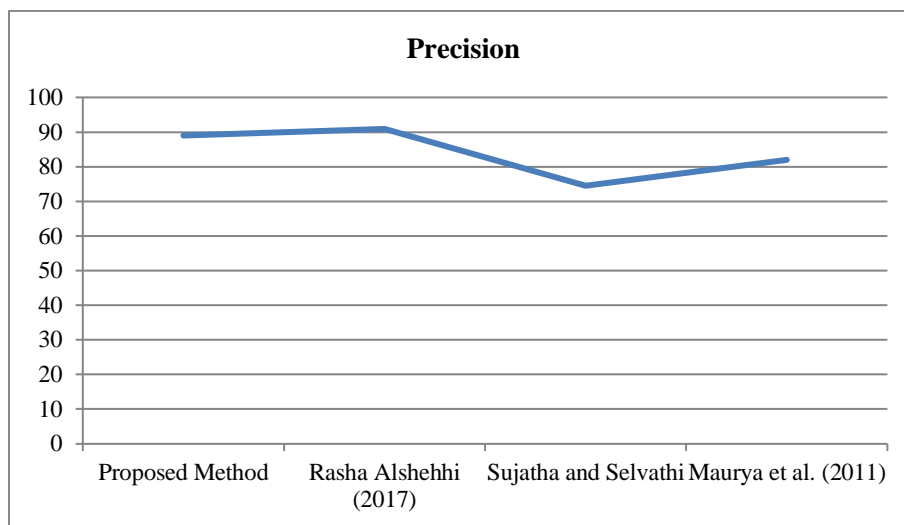


Figure 4: Comparative Precision of Recall with Existing Work

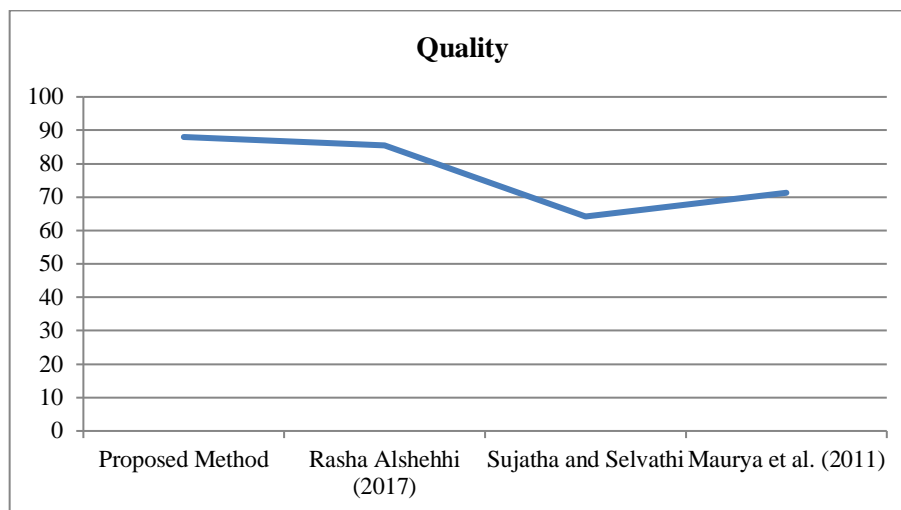


Figure 5: Comparative Analysis of Quality with Existing Work

5. Conclusion

In this research the image segmentation techniques used for image remote sensing are discussed and evaluated. It has been found that there is no perfect method for image segmentation because the result of image segmentation depends on many factors, i.e. Pixel color, consistency, intensity, image similarity, image content and problem area. The main objective of this research is the extraction of road space from the RSI. The extraction of road networks in remote urban areas of images plays an important role in many urban applications (eg road traffic, geometric correction of remote sensing images in cities, updating geographical information, etc.). Because of the complex geometry of buildings and the geometry of sensor detection, it is generally difficult to distinguish the road from its background.

In this work, a hybrid method is proposed for the extraction of paths from high resolution images based on the segmentation of the mean and HFT segmentation. The proposed method includes: noise suppression using the Lucy-Richardson algorithm, then a further improvement of the contrast between the initial segmentation of road and non-road pixels using the segmentation means k and finally HFT based segmentation.

Simulations are conducted on remote sensing images in urban, suburban and rural areas to demonstrate the proposed method and compare it with other similar approaches. The results show the validity and superior performance of the proposed extraction method.

The future enhancement of this research work in order to adapt the proposed method to work with infrared color images, multispectral images with additional information from a greater number of bands and low resolution or noisy images. In addition, we will also examine the results of the unsupervised method in the semi-supervised or supervised setting for object extraction.

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