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Application of Remote Sensing Techniques to Detect Roads and its Neighborhood by Using Graph-Based Algorithms

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ABSTRACT

The application of remote sensing techniques is widely used in the analysis of remote sensing objects. The extraction and analysis of roads using this technique provide efficient data for the stakeholders which can be utilized in various occasions. The road structures are always incubated with rich neighboring objects. The extraction and the segregation of these neighborhood objects is a challenging task. The rich set of image processing algorithms provides a flexible extraction of road and its neighborhood. This paper proposes a graph technique to extract the road and its neighborhood. The graph cut algorithm is applied to 4 sets of image datasets. The datasets are taken at different intervals. The paper is aimed at detecting the road and its neighborhood. The segmentation accuracy in detecting roads and its neighborhood is also discussed in the article.

Key words: Remote Sensing, Image Processing, Road and Its Neighborhood Segmentation, Graph Cut

1. INTRODUCTION

Remote sensing is the science of getting information about a remote object by using satellite technology. With the advancement in satellite sensors and cameras, nowadays remote sensing applications are not only limited to transportation, geology, agriculture, and urban planning. Remote sensing also plays a big role in the detection of road and non-road regions such as buildings, trees and vehicles etc. To detect the road from remote sensing images the following features are need to be considered. i) Geometric characteristics is the width of the same road and is almost constant. The edges are parallel to each other it is obvious that when it captures from the remote sensing mode the trees and buildings are also part of the road object. ii) Topological feature is the junction were road joins with another road network which can be seen more in cities. iii) Radiation characteristics of the road and non-road are same which exhibits some grey values. iv) Contextual feature is also called as background feature. The road from different places will have da different background (village road and road network in cities)[1].In this paper a Google earth image is captured and road extraction is done by using graph based algorithm.

The next two sections discuss the possible application and challenges of the road segmentation in remote sensing images.

In addition to monitoring desertification, floods, droughts, and changes in landforms, the remote sensing technique has become an efficient instrument for systematic surveying, analysis, and better management of natural resources (land, soil, water, forests, and mountains) [2]. It offers a wide range of opportunities to investigate, catalogue, and analyse the natural resources of underdeveloped areas. It uses satellite photos, typically, to capture the dynamic changes in physical processes and the resulting landforms. A general overview of remote sensing is given in this work. Although this method has been used to beaches, valleys, and other landforms, the focus of this essay is on its application to geography [3].

One of the most important jobs for contemporary transportation networks is road extraction. This assignment is typically challenging due to the complicated backgrounds, such as urban roads that are obscured by traffic, people, and the shadows of nearby trees or buildings, as well as country roads that have heterogeneous appearances with high and low interclass differences [4]. In this study, a unique technique is proposed for extracting roads from optical satellite pictures by means of a post-processing staged deep residual convolutional neural network (RDRCNN) [5]. A residual connected unit (RCU) and a dilated perception unit make up the RDRCNN (DPU). To provide outputs of the same size, the RDRCNN structure is calculated with symmetric values. For RDRCNN post processing, a tensor voting technique and a math morphology are employed [6]. To test the effectiveness of the suggested network architectures, experiments are done on two datasets of high-resolution data. The outcomes of the proposed architectures are then compared to those of other network architectures. The outcomes show how well the suggested strategy for extracting highways from a complicated image [7].

Road image processing is necessary to obtain finer image details. Transforming a black-and-white image into a colour image, conceal data within an image, and many other things. Filtering an image, enhancing an image, adding colour to an image, and many other processes are all included in the road image processing [8]. There are numerous methods available, such as filters and picture enhancement techniques, to obtain image details. In this system, that analyses photos or videos to improve them, identify items in them, identify people (so you can tag them on Facebook), track the lane of the road (for autonomous cars), and other things. Digital image processing can be described as a multidimensional system since images might have two or more dimensions [9]. Acquisition, augmentation, segmentation, feature extraction, and classification of images are the primary topics of image processing. The application of this technology is evident in a wide range of fields, from remote sensing to medicine. The development and widespread accessibility of image processing gear has increased the use of image processing even more. Computer vision and image processing enable machines to behave as eyes. Different types of sensors can be replaced by cameras. To is important to visualize the objects through eyes for analysis. The straightway approach for image acquisition could not able to serve this purpose, as the objects cannot be visualized in this raw image for analysis. So the majority of remote sensing applications rationale with at least one processing approach [10].

2. LITERATURE SURVEY

According to Xu et al. [11], a watershed dual-threshold and multi-weighted technique to extract urban roads has improved precision and better robustness. It is suggested by Ünsalan and Sirmacek [12] to identify road networks. The system is composed of three phases: probabilistic road centre recognition, road shape extraction, and creation of a road network based on graph theory. Following the graph refining procedure, they determine that all test images have a completeness, correctness, and quality score of 0.75, 0.74, and 0.59, respectively. Yecheng Lyu[13] compares the distributed LSTM layer and the convolutional layer in order to show the benefits of combining the CNN and LSTM structures for processing spatial feature maps. According to the test results on the KITTI road benchmark, our system gets an F1-score of 89.08 percent and an average precision of 91.60 percent. R. and Pankaj Pratap Singh1 Using adaptive global thresholding and morphological operations, D. Garg2 [14] followed a hybrid approach to extract roads from HRSI. Performance evaluation of the road network extraction in different areas of HRSI completeness and correctness is 98.95 and 98.94 for developed sub urban area and 98.89 and 99.78 for developed urban area. Afak Altay Açar1*, Afak Bayr2 "Road Detection Using Classification Algorithms"[15] that when he used 15X15(block size) KNN classifiers is more completeness than Naive Bayes classifiers but it has less ratio of correctness i.e. 82.87 and 33.08when he reduce block size(10X10) completeness decreases for k-Nearest neighbours algorithm [15]. They discovered that even with damaged and low-quality image data, satisfactory accuracy for the retrieved features could be attained. Here image 1 (degraded) scored 78.3, image 2 (noise unaffected) 87.7, image 3 (noise affected) 84.2, image 4 (poor resolution) scored 65.4, image 5 (without blurring) scored 92.1, and image 6 (with blurring) scored 90.8 for quality. In order to extract roads from high resolution panchromatic remotely sensed data, D. Chaudhuri, N. K. Kushwaha, and A. Samal[16] presented a directional morphological enhancement and segmentation techniques approach. The results show that the algorithm is quite accurate. The multi-step method uses both the spectral and spatial features of roadways. Road segmentation, hole filling, small region filtering, length-based region filtering, the tiny branch elimination method, and road segment connecting are the key elements in the algorithm. Panchromatic pictures from IKONOS, CARTOSAT-2A, Quick Bird, and Arial were used to evaluate the proposed algorithm. Inglada [17] offers a study using support vector machines to identify man-made items like roads and trains, emphasising that the findings indicate the potential for discriminating between several classes of objects with classification rates above 80%.

Table 1: Road Extraction Techniques

Algorithm	Road feature	Sample	Disadvantage	Performance accuracy or correctness (%)
ANN	Intensity, edge, spectrum	1–2	Discontinuity, noisy, over-fitting	95
SVM	Intensity, edge gradient, length, width	3–6	Require more samples, low precious	13–35
MRFs	Mean intensity value, texture	5	Manual intervention	63.5–93.4
Mean shift	Histogram of the HIS image	1–8	Over-segmentation, long literation time	86–90
Knowledge-based methods	Intensity, edge	2–4	Over-segmentation, susceptible to occlusion and shadow	70–79
Mathematical morphology	Geometric feature, direct of line	3–4	Discontinuity, susceptible to structural elements	91.76
Active counter model	Intensity gradient	3	Depend on the seed point selection	95–99
Filtering and group	Direct of line, intensity	2–6	Rely on the prior knowledge	80–98

Table 1 compares the various road extraction techniques for hyper-spectral images. This table comprises performance, road attributes, the number of test samples, and algorithms (Das et al., 2011) [18].

Each of the algorithms has pros and cons. It is challenging to achieve high detection accuracy for image segmentation with just one method. Therefore, various approaches and combinations of approaches should be used to study road extraction methods. Defining the road features is another major challenge in road extraction from RS data. The majority of the currently used techniques can effectively recognize roads as linear or narrow light bands. The road objects should be specified precisely since as image resolution increases, more intricate road characteristics and noise interference (buildings, shadows, and road impediments) will show. Therefore, a common problem of many researchers is how to create a decent road model and extract the road quickly and reliably.

3. METHODOLOGY

The road categorization can essentially be viewed using a pixel labeling task. A feature vector (p v) is used to represent the every pixel (p) in an input image. The pixel count N is used to represent an by using the groups of feature vectors with the notation $V_{(1,\ 2)}$ = N, where N stands for the picture's pixel count, can be used to represent an image. For a road input image, the experimentation objective for the detection of road segmentation is to discover a corresponding label set by assigning a label to each pixel in the image. Labels for pixels in the road region are set to 1, while labels for pixels in the background are set to 0. A road image is modelled by an s-t graph in graph-cut based algorithms [18]. There are two types of nodes and edges in an s-t graph. The next corresponding node and the destination nodes are the two different sorts of nodes in question. While the latter has an initial node s and a sink node t, the previous node corresponds to pixels in a road image. N-links are edges that connect nearby nodes, and t-links are edges that connect nearby nodes to terminal nodes [19]. Each edge is given a non-negative weight to represent link strength. The total weight of the edges in a cut determines its cost. The definition of cut defines the subset of each edge that need to be removed. In terms of picture segmentation, a cut separates the foreground and background into two distinct subsets of nodes in an s-t graph. The best segmentation of an image determines the cut with the lowest cost, which is also called a min-cut. The procedure of minimizing an energy function to find a min-cut can be formalized using the functions for R and L where R and L. It represents of the characteristics with its regional term. And each of these characters represents the individual node in the form of s-t graph, B and L is the term used for smoothness, with respect to the relationship between neighboring nodes, and a constant that denotes the relative weight of the two terms. The regional term has the following definition [20]. The p is a t-link weight that can be viewed as a fine for assigning label pl to a neighborhood p. The link's weight to the source node is also considered to be an accuracy factor. If every pixel is properly named, only then it should be the regional term and it always be the smallest. The link weight can often be determined using a probability distribution of the data. For instance, Rother et al. [21] modelled both the foreground and the background using Gaussian Mixture Models (GMMs) and defined function in a negative logarithm of the likelihood function of GMMs. However, GMMs make the unrealistic assumption that data follow the Gaussian distribution, which is untrue for complicated and dynamic traffic situations. In order to determine the feature selection and regression capabilities, we use it to estimate link weight or the t-link weights. Following is the definition for link weights [22]. The N is a set made up of adjacent pixel pairs, and we can define a function that takes the values 0 and 1 for the foreground and background conditions respectively. The penalties also exists at the foreground/background boundary, as an n-link weight, which shows how similar two adjacent pixels p and q are to one another. The pixel p and q is typically defined in the graph-cut based segmentation algorithms [23]. A constant can be defined that can be calculated from the average contrast across an image [24]. Evidently, assigning different labels to two adjacent pixels with high similarity results in a significant penalty, whereas labelling two pixels with strong contrast differently results in a low penalty.

4. EXPERIMENTATION

Road surfaces can exhibit significant intra-regional variability. Because of varying lighting, shadows, weather, various types of road surface materials, lane markers, and other factors, the appearance of road surfaces is complex and subject to change. As seen in Figure. 2, contrast on road boundaries is not as great as desired, but contrast on pixels on both sides of lane marking edges or shadow margins generates strong contrast. In fact, contrast near the edges of roads is frequently significantly weaker than it is in some of the subregions of road areas. As a result, when n-link weights are determined by (4) as in earlier graph cut approaches, the min-cut may differ from the actual road limits. Only when the min-cut happens at the road boundary should the energy function and is minimized from the perspective of constructing energy functions for road segmentation. As a result, finding alternative methods to establish n-link weights is important rather than just using nearby contrast as in (4). Finding the relationships between the features of surrounding pixels and the n-link weights is the key. An intuitive method is to automatically learn these mapping relationships using data, such as labeling the maximum number of road features in the corresponding input images. The more the labeling more road-like structures can be detected.

In order to gain valuable information from the input image, it requires to go with some prepressing stages as the road shows some elongated geometric features with gradually changing grey values in the input image.

Large differences in the apparent look of a road (spectral reflectance, object shadow, occlusion, and contrast) make image segmentation more challenging. To assess the best input image for the feature treatment a series of image data set was chosen in the experimentation taken from different organization shown in Table 2 and Figure 2.

For various requirements, the road width is designed at various levels. All roads, of varying widths and lengths, cross one another.

The following parameters were used in the experiments: a = 0.5, b = 0.5, Wp,s = 0.8, and Hground = 1 m. Figure 2 displays the road extraction findings, including the overall performance and specific results for the datasets. The condition is depicted in Figure “2a” to “2h”. Table 2 contains a list of the quantitative evaluation of road extraction. On Dataset 1, the proposed method's accuracy was 100%, but its recall was just 87%. The Dataset 2 results were thorough and reliable, with the best F1 score being 0.93. The performance of the suggested approach on the Dataset 3 was the worst, with a precision of 84%, while the result on Dataset 4 had the best recall of 95.8%. Dataset1 had the lowest time cost and Dataset 4 had the highest since the time cost is directly correlated with the length and complexity of the scene. The findings demonstrate that the suggested strategy was effective for automatically localizing and extracting roadside trees in scenarios of different complexity.

IoU is the ratio of the intersection and union of the extracted bounding box to the matching ground truth, where TP is the number of correctly extracted roads, FN is the number of roads that were excluded from the results, FP is the number of roads that were wrongly extracted, and so on. The width of the roads served as a representation of the extension of the road positions. Only when there were less meters between a road genuine location and its detected location and the IoU was more than 0.8 was road extraction deemed effective.

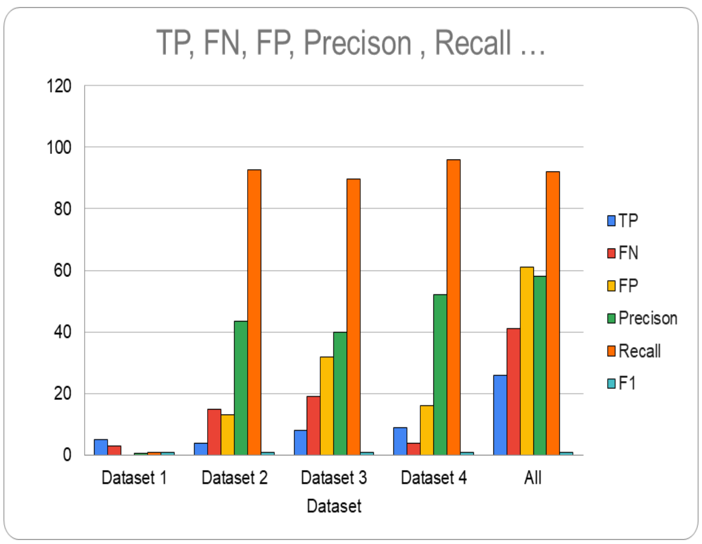

Figure 1: Quantitative evolution of road extraction

Table 1: Accuracy assessment for road extraction

Dataset	TP	FN	FP	Precision	Recall	F1
Dataset 1 Landsat 7	5	3	0	50%	87%	0.9
Dataset 2 Google Earth Pro	4	15	13	43.6	92.7	0.9
Dataset 3 Sentinel	8	19	32	40	89.8	0.9
Dataset 4 Landsat8	9	4	16	52	95.8	0.9
All	26	41	61	58	92	0.9

5. CONCLUSION

The four different input datasets were used in this experimentation. The location of the data is the Mangaluru region of Karnataka, India. Datasets are acquired from Landsat 7, and 8. Also a set of images from Google Earth and Sentinel satellite were used to for the experimentation. The objective of using different sets of images is to test the efficiency of road detection. The graph cut algorithm was applied for these datasets to detect the road and its neighborhood. Different segmentation statistics of the graph cut algorithm is shown in table 1 and fig. 1. It is observed that for some of the input images it is hard to detect the roads. Some nearby objects of the road also treated as roads which increase the value of the confusion matrix as shown in Table 2. A machine learning road and its neighborhood detection model may be used to increase the segmentation accuracy.

Figure “2a”, “2c”, “2e”, “2g” is an input image taken from Landsat 7, Google Earth, Sentinal, and Landsat 8. The successive output generated using Graph Cut algorithms are shown in the Figure “2b”, “2d”, “2f”, “2h”.

In dataset 1, the graph cut algorithm could able to detect the road network up to some accuracy. But here it fails to detect the other neighborhoods.

The dataset 2, completely fails to detect other neighborhoods as seen in the output.

In dataset 3, it is able to detect other neighborhoods. But the road detection could be able accurate, it gives falls details as the road attachments also look as the road in the output.

Dataset 4, able to detect other neighborhoods. But. the road detection could be able accurate, it gives falls details as the road attachments also look as the road in the output.

Figure 2 a : Input Image 1 from Google Earth Pro LandSat 7

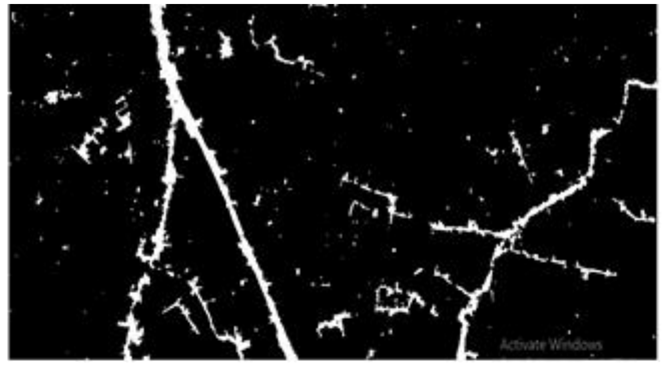

Figure 2 b: Output Road and Neighbourhood (some buildings)Segmentation using Graph Cut.

Figure 2 c : Input Image 2 from Google Earth

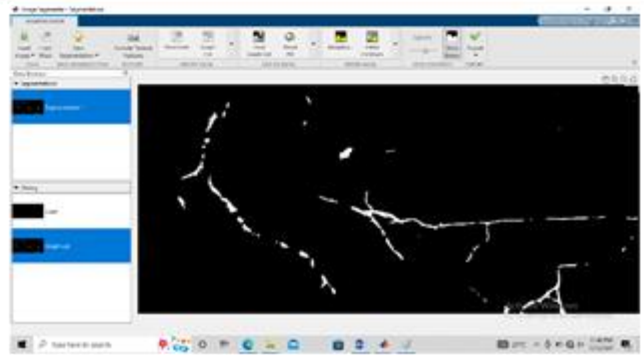

Figure 2 d : Output Only Roads are detected for this input image using Graph Cut.

Figure 2 e : Input Image 3 from Sentinel

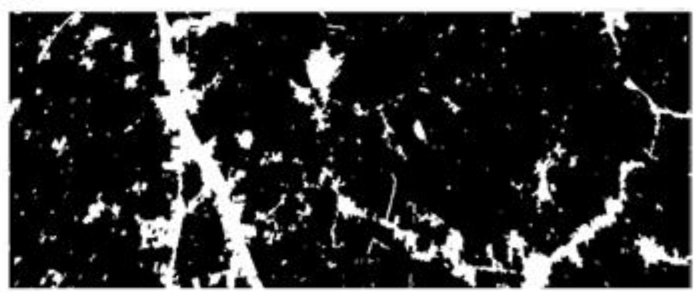

Figure 2 f: Output Road and Neighbourhood (some buildings, open land and forests)Segmentation using Graph Cut

Figure 2 g : Input Image 4 from LandSat

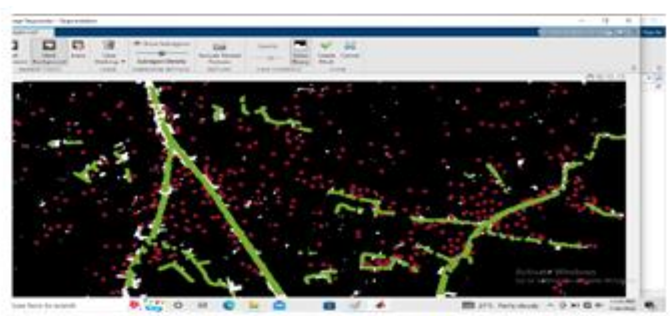

Figure 2 h : Output Road and Neighbourhood Segmentation using Graph Cut.

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