AUTOMATIC MAIN ROAD EXTRACTION FROM HIGH RESOLUTION SATELLTE IMAGERY

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ABSTRACT

Road information is essential for automatic GIS (geographical information system) data acquisition, transportation and urban planning. Automatic road (network) detection from high resolution satellite imagery will hold great potential for significant reduction of database development/updating cost and turnaround time. From so called low level feature detection to high level context supported grouping, so many algorithms and methodologies have been presented for this purpose. There is not any practical system that can fully automatically extract road network from space imagery for the purpose of automatic mapping. This paper presents the methodology of automatic main road detection from high resolution satellite IKONOS imagery. The strategies include multi resolution or image pyramid method, Gaussian blurring and the line finder using 1- dimemsional template correlation filter, line segment grouping and multi-layer result integration. Multi-layer or multi-resolution method for road extraction is a very effective strategy to save processing time and improve robustness. To realize the strategy, the original IKONOS image is compressed into different corresponding image resolution so that an image pyramid is generated; after that the line finder of 1-dimemsional template correlation filter after Gaussian blurring filtering is applied to detect the road centerline. Extracted centerline segments belong to or do not belong to roads. There are two ways to identify the attributes of the segments, the one is using segment grouping to form longer line segments and assign a possibility to the segment depending on the length and other geometric and photometric attribute of

the segment, for example the longer segment means bigger possibility of being road. Perceptual-grouping based method is used for road segment linking by a possibility model that takes multi-information into account; here the clues existing in the gaps are considered. Another way to identify the segments is feature detection back-to-higher resolution layer from the image pyramid.

1.INTRODUCTION

Modern digital technology has made it possible to manipulate multi-dimensional signals with systems that range from simple digital circuits to advanced parallel computers.

The goal of this manipulation can be divided into three categories:

- Image Processing image in → image out
- Image Analysis image in → measurements out
- Image Understanding image in → high-level description out Here we will focus on the fundamental concepts of image processing. Image understanding requires an approach that differs fundamentally from the theme of our discussion. Further, we will restrict ourselves to two–dimensional (2D) image processing although most of the concepts and techniques that are to be described can be extended easily to three or more dimensions. We begin with certain basic definitions. An image defined in the "real world" is considered to be a function of two real variables, for example, a(x,y) with a as the amplitude (e.g. brightness) of the image at the real coordinate position (x,y). An image may be considered to contain sub- images sometimes referred to as regions–of–interest, ROIs, or simply regions. This concept reflects the fact that images frequently contain collections of objects each of which can be the basis for a region. In a sophisticated image processing system it should be possible to apply specific image processing operations to selected regions. Thus one part of an image (region) might be processed to suppress motion blur while another part might be processed to improve color rendition. The amplitudes of a given image will almost always be either real numbers or integer numbers. The latter is usually a result of a quantization process that converts a continuous range (say, between 0 and 100%) to a discrete number of levels. In certain image-forming processes, however, the signal may involve photon counting which implies that the amplitude would be inherently quantized. In other image forming procedures, such as magnetic resonance

imaging, the direct physical measurement yields a complex number in the form of a real magnitude and a real phase.

2.LITERATURE SURVEY

Because of its significant applicability, automated road information extraction from satellite and aerial imagery has been an important subject of research in remote sensing. The current effort is particularly interested in road network extraction using pattern recognition approaches. The reason is that most applications involved in safety, hazards, and disaster assessment requires detailed and accurate representations of road networks, which can only be obtained from high resolution images. However, these types of images are mostly panchromatic, such as Digital Orthophoto Quadrangles (DOQ) from U.S. Geological Survey (USGS), and one-meter resolution IKONOS images from Space Imaging. Their spectral signatures are weak and cannot be effectively utilized to identify road features. Instead, image interpretation has to rely on image texture, shapes, patterns and changes of local image intensity. In the last twenty years or so, a variety of extraction methods have been developed. Some of them can be generally applied for linear feature extractions, while others are particularly designed for the road extraction task. The report classifies these methods into five categories: ridge finding, heuristic reasoning, dynamic programming, statistical tracking, and mapmatching. It is worth noting that such a classification is mainly for generalization and convenience of description. Actually, it is very difficult to classify some of these methods into specific categories. For instance, some of the existing algorithms may use a combination of different methods. And in some other cases, a method may fall into several method categories.

2.1. Ridge Detection

Intuitively roads are linear features that are shown as ridges or valleys on an image. Therefore road finding can also be considered as a task of ridge finding. The procedure developed by Nevatia and Babu (1980) is a classic one, which starts with the convolution of an image with a number of edge filters to obtain edge magnitude and direction, then goes through a thresholding and thinning process in order to delineate edge pixels, and finally connects the delineated edge pixels to form linked line segments. Gradient Direction Profile Analysis (GDPA) (Wang et al.1992; Gong and Wang, 1997) is another representative method used for ridge finding. This method first calculates the gradient direction for each pixel, which is defined as thedirection of maximum slope among the four defined directions near the pixel. As the ridge direction has the same direction as a road segment or a linear segment, and it is perpendicular to the gradient directions of the pixels with the ridge, an analysis of the gradient profile will generate the ridge pixels, which correspond to the highest points of the profile. Linking the ridge points then produces the ridgelines, or in the road detection case, the road segments. The concept of differential geometry has also been applied to ridge detection (Steger, 1996). This method uses curve or surface fitting techniques to derive ridge locations on an image. Once the image intensity surface is represented with a mathematical equation, the first and the second derivatives of the equation can be analyzed to locate ridgelines. Image filtering methodshave also been extensively discussed in the literature for edge or ridge delineation. Most frequently referenced methods in this category include Canny's edge detector (Canny, 1986) and Marr and Hildreth's zero crossing operator (Marr and Hildreth, 1980). These methods filter out the low frequency information in the image and preserve the high-frequency structures, such as roads, which are particularly useful for high-level recognition of road networks because through image filtering, a large amount of information that is irrelevant to road recognition can be thrown away at the very beginning, and then image analysis can focus on these structures that contain road networks.

2.2. Heuristic Method

The heuristic method makes use of a reasoning process similar to the human vision system. Sometimes it is also referred to as rule- or knowledge-based method. Melsels and Mintz (1990) considered a three-stage reasoning concept and applied the concept to road network extraction: a low-level stage that deals mainly with pixel segmentation, a high-level stage that models and labels feature objects, and an intermediate level of representation that interfaces between low level and high-level processing. Image primitives that are considered as building blocks of roads are first identified with pixel value checking at neighborhood levels. Intermediate level analysis will combine image primitives into line segments with the use of some reasoning mechanism (e.g., how far the combined primitives are apart; what directions each of the primitives follow; whether they parallel with each other; etc). High level processing allows further gap filling and segment grouping by considering distances, brightness, and uniformity among the grouped tokens and gaps between them. One of the advantages of the heuristic approach is in its flexibility in dealing with problems such as linear feature alignment and fragmentation. For example, McKeown and Pane (1985) suggested that trend and the relative distances between fragments can be utilized as factors while fragmented primitives are aligned and connected. With some extension, McKeown and Denlinger (1985) also developed a road tracking system that relies on road texture correlation and road edge following alternatively: when one fails, the other will be utilized. Later, Mckeownet al (1992) and (Zlotnick, 1993) introduced methods that track roads by searching for antiparallel edges as starting points for road tracking and linking.

2.3. Dynamic Programming

Dynamic Programming (DP) has been frequently utilized in road network extraction and has been described in detail by Gruen and Li (1996). The most appealing aspect of the method is that the road recognition problem can be formulated as an optimization program, and the solution to this program will result in the delineation of the road pixels. According to Gruen and Li, roads can be modeled with a set of mathematical equations. That is, derivatives of the gray values in the direction normal to the roads tend to be maximized, while derivatives along the road direction tend to be minimized. At the same time, roads tend to be straight lines or smooth curves, normally circular arcs, and their local curvature has an upper bound. These properties, then, can be characterized with a merit function, which can be solved using the DP technique. The introduction of the DP technique in pattern recognition dates back to the late 1960s. Since then, the technique has been used on raw images for pixel based processing (e.g., Montanari, 1970), and also used on tokens that are based upon higher level representations (Fischler et al, 1981; Geman and Jedunak, 1996). The technique is considered to be a good approach to finding curves in noisy pictures, because it can bridge weakly connected feature elements automatically while the program searches for optimal solutions. This property is also preserved when applied to the grouping of feature elements with higher level of representations. In either case, regulatory constraints can be utilized to derive curves that will meet certain predefined geometric requirements (e.g., smoothness or curvature). More importantly, DP provides a way to serialize the optimization procedure to allow computationally attainable solutions.

2.4. Statistical Inference

Due to complexities of road images, an ability to handle uncertainties (e.g., bridge crossing, road width changing, cars and shadows on the roads, image noises, etc.) is essential. For this reason, statistical models are particularly attractive for road image representation. Cooper (1979) first came up with the idea of modeling a blob boundary or a linear feature as a Markov process. Based upon this modeling scheme, he was able to use maximum likelihood estimation to derive the boundary representation that has the same formulation as other deterministic methods. The underlying significance of Cooper's scheme is that it provides an elegant and effective methodology for incorporating uncertainties into the linear feature recognition process. Barzohar and Cooper (1996) explored the idea further and developed a stochastic approach that can be more sophisticatedly applied to automatic road finding. This approach makes use of the so-called geometric-stochastic model that formulates road width, direction, gray level intensity, and background intensity as a stochastic process using the Gibbs Distribution. Then road detection is achieved through the maximum a posteriori probability (MAP) estimation. The method demonstrated promising results and can be further extended to consider possibly many other types of uncertainties in road extraction. A more recent study by Yuille and Coughlan (2000) provides additional enhancements to Barzohar and Cooper's approach. This study not only allows the analysis of the time and memory complexity in the MAP estimation, but also the determination of whether roads are detectable in a given image. The work of Geman and Jedynak (1996) is also based upon a statistic model that tracks roads through hypothesis testing. Their approach uses the testing rule that is computed from the empirical joint distributions of tests (matched filters for short road segments) to determine whether the hypothesis (road position) is true or not. The tests are performed sequentially and a uncertainty or entropy minimization procedure is devised to facilitate testing decisions, so that new tests can be analytically identified. The method appears to work reasonably well on low resolution images, but likely adaptable to high resolution images as well.

2.5. Map Matching

The rationale behind map matching in road extraction is that there already exists a largeamount of data on road systems in many parts of the world, especially in the United States. Once in house, this data can serve as a starting point for road network extraction. There are many advantages to combining remotely sensed data with existing databases (Wang at al.,1992). That is, existing data can be used as the interpretation key at the beginning, then verified, or updated, and the attributes of existing network can be also transferred to the newlyupdated network. The map matching approach has been explored by several researchers (Maillard and Cavayas, 1989; Stilla, 1995; Fiest et al., 1998; Zafiropoulos, 1998). Maillard and Cavayas first introduced the map-matching approach. Using this approach, they established a road updating procedure that consists of two major algorithms. The first algorithm focuses on image-map matching to identify roads that can be found on the map and the image. The second algorithmis then to search new roads based upon the assumption that these new roads are connected to the old ones. This approach was studied further and applied in different geographic settings (Fiset and Cavayas, 1997). To overcome some of the map matching problems of this approach, Fiset et al (1998) used a multi-layer perceptron based upon template matching to improve its performance further. Stilla developed a syntax-oriented method to use the map knowledge as a supportive aid for image interpretation. In this study, representations of road network structures are first obtained through map analysis. Then image object models are defined and utilized to search for objects that fulfil model expectations with a given tolerance. Assessment on image objects with respect to its correspondence to the map representations results in road object identification for a given image scene. Zafiropoulos (1998) considered the concepts of deformable contours, BSpines, Ribbon Snakes and presented a mathematical-modeling-based road verification and revision framework. With this framework, road centerlines are localized using a global least square adjustment.

2.6. Summary

From the above review of the existing methods on road network extraction, several observations can be made. First, the concept for road network extraction is relatively simple. That is, roads are shown as ridges and valleys; image intensity changes little along a road, but change drastically while cutting across a road; road direction changes tend to be smooth and have a upper bound; and roads follow some topological regularities in terms of connectivity among themselves. Basically, many of the existing methods make use of one or several of these characteristics. Second, reliable road network extraction remains a difficult task, and there exists no algorithm sufficiently reliable for practical use (Geman, and Jedynak, 1996). This is primarily due to the fact that the real world is too complex, and many of the existing tools can only handle very specific cases. Some may be able to handle more complex situations, but still can not be compared with a trained human operator. Mathematical models such as statistical models and dynamic programming have enhanced the ability to deal with this complexity significantly, but factors such as computational performance, implementation difficulty, and limitation of sophistication make more ambitious efforts difficult. Theoretically, a road recognition algorithm can consider all possible listed road characteristics. Practically, a road recognition algorithm canonly consider a limited set of characteristics, and when these characteristics change beyond a limit, the algorithm may fail. Finally, even though automated road extraction is a difficult problem to solve, improvement has been constantly made and there are still opportunities to be explored to further improve its performance. It appears that the semi-automated and the map-matching-based approaches tend to be more practical for short-term implementations. In the long run, studies of road image characteristics, their changes with respect to geographic background, image types, image resolutions, and development of mathematical models to represent these characteristics are critical in order to make substantive progress in this area.

3. OUTPUT SCREENS

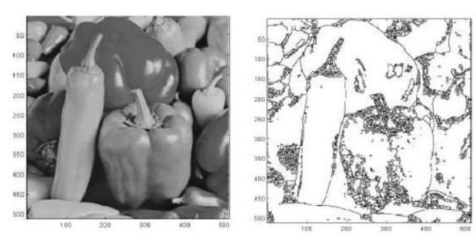
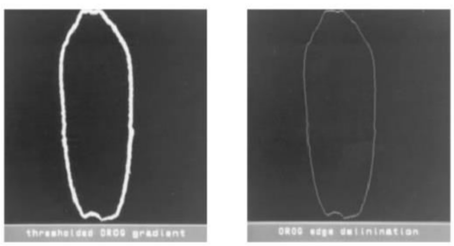


Figure 3. 1 Watershed image segmentation of the peppers_mon image.

(a) Original



(b) Edge map (c) Thinned edge map

Figure 3-2 . Boundary detection image segmentation of the projectile image.

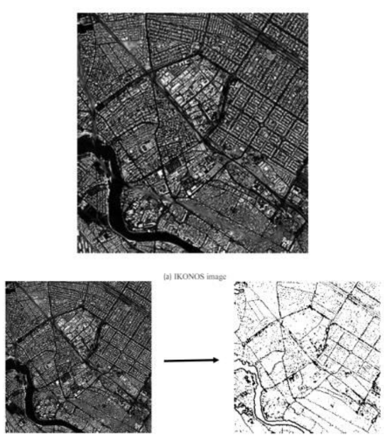


Figure 3.3 . Binary detection from IKONOS image after thresholding (19).

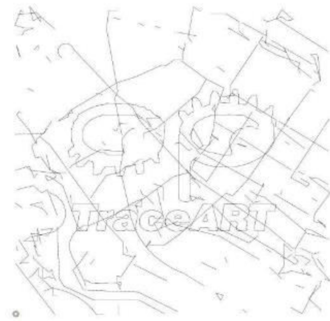


Figure 3.4 .(a) Extraction result

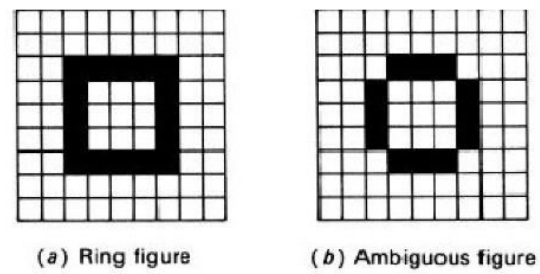


Figure 3.5 Connectivity.

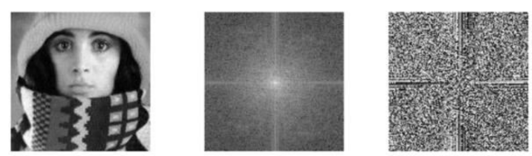


Figure 4a Original Figure 4b $\log(|A(,\Omega,\Psi)|)$ Figure 4c $\Phi(\Omega,\Psi)$

4. CONCLUSION&FUTURE WORK

Main road (centerline) extraction from high resolution satellite image is very useful for GIS database revision, change detection, and some applications that transportation infrastructure information, such as disaster management, urban planning plays an important role. Presented method in this paper is trying to automatically extract the prior defined main road centerline. The hierarchical grouping strategy applied could reliably extract most of main road centerlines in the open rural areas even though there are some occlusions (caused by clouds, trees etc).The method attempts to simulate the perceptual capability of human vision system to find salient linear feature from image. The experimental result indicates the potential utility of the method. For complex scenes, more information should be integrated in order to obtain more robust result. For acquiring more reliable result (no wrong extraction), we should take more road type (means more profile template) and more reliable verification algorithm into account, that can be done by combining kinds of template types and more segment attributes together for line detection and final assessment. Future work also includes extend the main road extraction to full road network extraction, because the main road network is very strong indication and contextual information for smaller road extraction and identification.

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