Towards Knowledge-Based Extraction of Roads from 1m-resolution Satellite Images

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Abstract

As IKONOS satellite with 1m-resolution camera has been launched in 1999, mapping using space-borne images will be a hot issue in computer vision area as well as photogrammetry, mainly because most of major man-made objects of interest can be identifiable. One of the automatically identifiable objects of importance may be roads. Detecting roads using edge detection approaches may be very difficult because a number of edge elements from such as buildings, etc. can be generated from edge detector. In this paper, we propose a method for the extraction of approximated road regions based on region segmentation that utilizes region information. Our method consists of the following three steps. First, an image is segmented using the modified hierarchical multi-scale gradient watershed transformation. Then, the road candidates are identified using information about road – gray level, elongatedness and connectedness. The identified road candidates are expanded by connecting the close-by roads knowing that roads are connected objects. Our method was tested on the simulated space-borne images and the result shows that the automation of road extraction is quite promising.

1. Introduction

IKONOS, which is the first commercial 1m-resolution satellite, has been successfully launched in 1999 and also, several 1m-resolution satellites are being launched within few years. The availability of such high-resolution satellite images may change the mapping, photogrammetry and remote sensing world. Because the shortcomings of airborne photogrammetry, such as small coverage, difficulties in periodical acquisition may be overcome and many objects that were not identifiable in low-resolution (10-30m) may be detected in high-resolution images. One of major objects that can be extracted from the images is roads that consist an important layer of vector maps. Extracting roads is so far done using high-resolution airborne images or low-resolution satellites images for highways or wide roads. Hence, algorithms for 1m-resolution images can hardly be found in literatures.

There have been intensive efforts to detect roads from low-resolution satellite and low-resolution airborne images. Fischler tried to detect road and "line-like" structures appearing in low-resolution (10-20m) aerial imagery [1]. Nathan introduced an estimator that was robust and statistically efficient to detect straight or circular pieces of roads in noisy low-resolution aerial images [2]. Donald proposed an approach for tracking roads from satellite images [3]. Zlotnick described a road finding system based on the road hypotheses [4]. However, because low-resolution images were assumed in these methods, roads were represented as a "line-like" structure.

Roads can be defined as long "line-like" objects at least in low-resolution satellite images even if there are curve-like roads[1]. However, roads are not line any more in 1m- resolution images. Rather, roads are ideally long rectangular objects. Indeed, as shown in figure 1b, it is difficult to detect roads by extracting long lines from images. In this case, roads extraction problem may be considered as finding long rectangular regions. However, true satellite images look more complicated because other objects such as trees beside of roads and shadows of buildings (See Fig 1a) exist. Also, the brightness of roads in the satellite images is usually dark if they are covered by asphalt and bright if they are covered by cement. However, utilizing only brightness values may result in poor road detection performance because there are a lot of objects that have similar gray levels to those of roads. In this paper, we propose a knowledge-based algorithm that utilizes *a priori* information – the gray level, road shape,

[1] We assumed the curved-roads could be found by extending "line-like" roads.

Figure 1. Simulated Satellite Images.

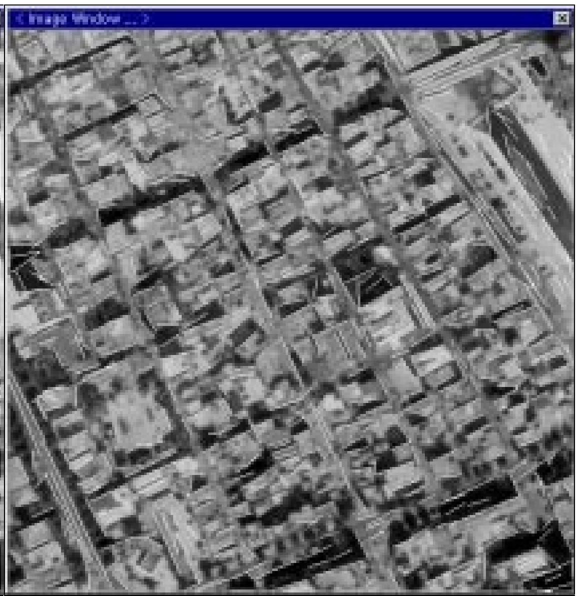

Figure 2. Line detected Image (Length > 15 pixels).

and their directions that can be extracted from the primarily segmented regions using watershed algorithm [5].

Our method consists of the following steps.

1. An image is segmented using the modified hierarchical multi-scale gradient watershed transformation.
2. The approximated road regions are identified using information about roads – gray level and elongatedness.
3. The identified approximated road regions are expanded by connecting the close-by roads knowing that roads are connected objects.

In Section 2, the watershed algorithm that we have modified, knowledge extraction and rule-based road detection will be described. In Section 3, the result will be reported. The current problems and the future work will be described in Section 4.

2. Knowledge-based Road Detection

2.1 Watershed-based Primary Segmentation

As stated in Section 1, the first step is to primarily segment into meaningful regions. Usually, the region-based segmentation suffers from over- and under-segmentation problem. Our requirements for primary segmentation are 1) road regions should be segmented into not too many elongated regions along the road directions and 2) road regions should not be merged with non-road regions. To achieve the purposes, we used watershed algorithm. In the watershed algorithm, grayscale images are considered as topographic reliefs and the numerical value of each pixel stands for the elevation at this point. Regional minima correspond to lakes where a drop of water on topographic surface swiftly descends and eventually reaches. The topographic surface where a drop of water descends is called catchment basins and the lines separating catchment basins is called watershed lines. The region segmentation is, then, to finding the watershed lines in the transformed topographics surface.

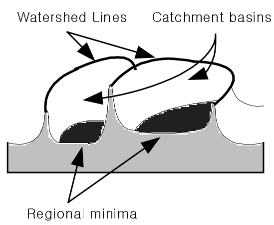

Figure 3. Topographic surfaces.

However, the over- or under- segmentation is well known problem of the watershed algorithm [5, 6]. As shown in figure 4 (b), the image was segmented into a lot of meaningless regions if we applied the watershed algorithm to the original or the less blurred version of the original image and the road regions have been merged with non-road regions when blurring level was high. To solve this problem, many approaches such as marker functions [6], mathematical morphology [6] and multi-scale space are used [7]. In this paper, we developed a modified hierarchical multi-scale gradient watershed algorithm to segment 1m-resolution satellite images.

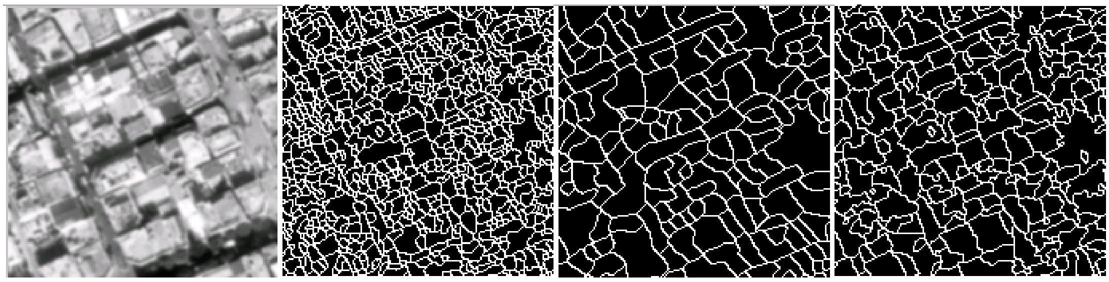

Figure 4. (a). Simulated 1m-resolution satellite images. (b) Watershed results (blurring level 0). (c) Watershed results (blurring level 3). (d) Our watershed results (blurring level from 0 to 3).

Because the Gaussian blurring has attractive properties simplifying images into a well-behaved manner, we adapted Gaussian blurring for multi-scale space images [7]. At a low blurring level, as shown in figure 4 (b), the boundaries of objects in images are accurate but the image is over-segmented. In the other hand, when the blurring level was high, the images were under-segmented but as shown in figure 4 (c), the boundaries of objects in images are mismatched with that of segmented regions. This may affect on the region feature calculation in Section 2.2. Therefore, to achieve a good primary segmentation, the advantage of each blurring levels should be combined. Hence, we modified the multi-scale approach by Gauch [7] that was used for semi-automatic segmentation.

Figure 5 is the flow chart for the modified hierarchical multi-scale gradient watershed algorithm. Firstly, to generate scale-space images, we apply Gaussian blurring from blurring level 0 to n to the original image and n blurred images with different blurring levels are generated. Secondly, we calculate the gradients of each image using a Sobel operator. After the gradient images are generated, we apply watershed transformation [7] to each gradient image. Finally, we merge regions in the blurring level 0 image with the blurring level 1 image based on the region boundaries extracted from the blurring level 1 image. We merge the resulted regions from the previous merging step based on the region boundaries which were resulted from watershed transformation of the blurring level 2 image. The region merging is performed up to blurring level n image. The merging rule is that the regions segmented from the lower blurring level image are merged if the centroids of those regions fall into the same region in the upper level image. The boundaries are kept from the region boundaries generated from the lower blurring level. In this way, we can reduce the over-segmentation and the boundaries of regions can be well matched with those of the corresponding objects (See Fig 4d). The next step will be to select possible road regions from the primarily segmented regions as discussed in the following sections.

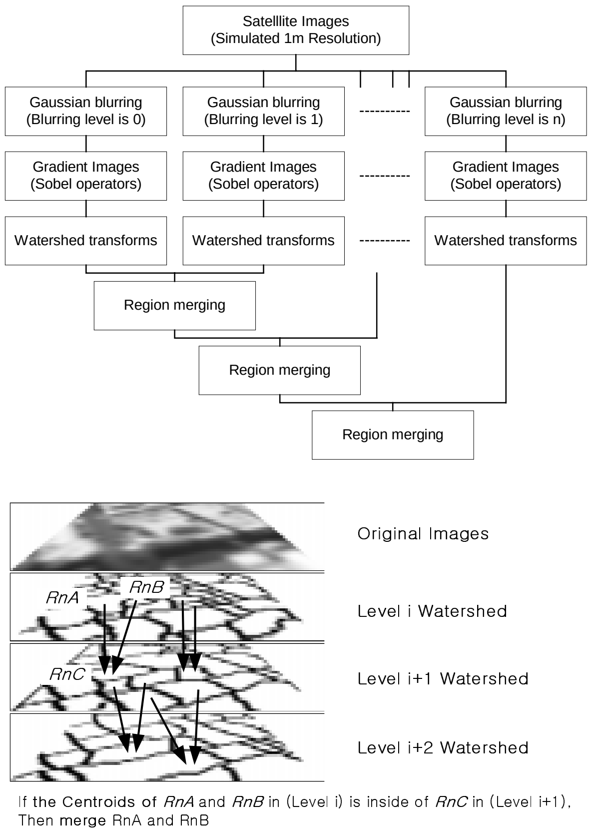

Figure 5. (a) The flowchart of the modified hierarchical multi-scale gradient watershed algorithm. (b) The region merging rule.

2.2 Knowledge Extraction

The roads appear dark (asphalt road) or bright (cement) in the satellite images. Hence, the gray level of the region is one of information to extract road regions. We used average gray level to reject non-road regions. However, there are many objects with the similar gray level. The gray level alone can not distinguish roads from other objects. In addition to that, we utilized the shape information called elongatedness. In order to calculate the elongatedness feature, the major axis of each region should be assessed as follows.

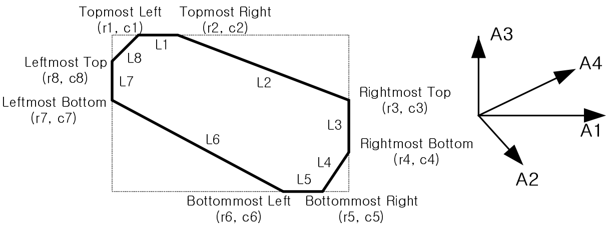

Figure 6. The calculation of major axis orientation.

2.2.1 Major Axis Calculation

As shown in figure 6, every region has at best distinct extremal points which lie on the normally oriented bounding rectangle. Let R be the given region, the coordinates of the extremal points can be defined as below.

$$
\begin{array}{ll}
r1 = r2 = r\min & r5 = r6 = r\max \\
c1 = \min\{c \mid (r\min, c) \in R\} & c5 = \max\{c \mid (r\max, c) \in R\} \\
c2 = \max\{c \mid (r\min, c) \in R\} & c6 = \min\{c \mid (r\max, c) \in R\} \\
r3 = \min\{r \mid (r, c\max) \in R\} & r7 = \max\{r \mid (r, c\min) \in R\} \\
r4 = \max\{r \mid (r, c\max\} \in R\} & r8 = \min\{r \mid (r, c\min\} \in R\} \\
c3 = c4 = c\max & c7 = c8 = c\min \\
{*}\, r\min \text{ is the topmost row.} & {*}\, r\max \text{ is the bottommost row.} \\
{*}\, c\max \text{ is the rightmost column.} & {*}\, c\min \text{ is the leftmost column.}
\end{array}
$$

Also, we can define the line segment lengths and the length of the four axes denoted by A1, A2, A3 and A4 as below.

$$
\begin{array}{ll}
L1 = |c1 - c2| + 1 & \\
L2 = \sqrt{(r2 - r3)^2 + (c2 - c3)^2} & A1 = \dfrac{(L1 + L5)}{2} \\
L3 = |r3 - r4| + 1 & \\
L4 = \sqrt{(r4 - r5)^2 + (c4 - c5)^2} & A2 = \dfrac{(L2 + L6)}{2} \\
L5 = |c5 - c6| + 1 & A3 = \dfrac{(L3 + L7)}{2} \\
L6 = \sqrt{(r6 - r7)^2 + (c6 - c7)^2} & A4 = \dfrac{(L4 + L8)}{2} \\
L7 = |r7 - r8| + 1 & \\
L8 = \sqrt{(r8 - r1)^2 + (c8 - c1)^2} &
\end{array}
$$

In these four axes, the one having the largest length is the major axis. The orientation angle for A1 is 0° and the one for A3 is 90°. Also, the orientation angle for A2 and A4 is defined as below respectively.

$$
\theta_2 = \frac{1}{2A_2}\left[L2\tan^{-1}\frac{r2 - r3}{-(c2 - c3)} + L6\tan^{-1}\frac{r7 - r6}{-(c7 - c6)} \right]
$$

$$
\theta_4 = \frac{1}{2A_4}\left[L4\tan^{-1}\frac{r4 - r5}{-(c4 - c5)} + L8\tan^{-1}\frac{r1 - r8}{-(c1 - c8)} \right]
$$

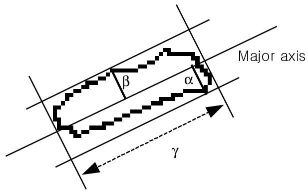

Figure 7 Elongatedness Calculation.

2.2.2 Elongatedness

The elongatedness can be calculated using the major axis. In figure 7, we first find the major axis of a region. Then, we find two boundary points such that the points lie on upper and lower sides of the region boundary and the points are the longest from the major axis. Let α, β be the lengths from those points to the major axis and let γ be the length of the major axis. Then, the elongatedness can be calculated as follows.

$$
elongatedness = \frac{\alpha + \beta}{\gamma}
$$

2.2.3 Rule-based Road Candidate Selection

The non-road regions are deleted or merged based on the region features by following rules.

Rule 1: If the size of a region is less than _SIZE pixels, then the regions are merged with the adjacent region among which shares the longest region border.
Rule 2: If the average gray level of a region is greater than _MIN and less than _MAX, then the region is removed.
Rule 3: If the difference between the directions of the two adjacent regions is less than _DIFF, then two regions are merged.
Rule 4: If the length of the major axis of a region is shorter than _SIZE pixels, then the region is deleted.
Rule 5: If the elongatedness of a region is less than _SIZE, then the region is deleted.

2.3 Road Expansion by Directional Cone Search

In the previous step, non-road regions can be filtered out. However, due to the imperfection of the primary segmentation, true road regions may be deleted or undetected (See Fig. 9) or some falsely detected road may exist so that there are disconnected roads and noises.

Hence, the disconnected roads are reconnected and the falsely detected roads should be deleted using the detected road regions.

We used the directional searching algorithm. The algorithm consists of the following steps.

1. From a detected region, we shoot two cones of which directions are the direction of the region.
2. The cone may meet several regions. Then, we choose the most probable road region and connect two regions by adding regions between two regions.
3. Repeat Step 1-2, until no more reconnection occurs.

Using the above steps, the disconnected road regions can be connected.

3. Result

Even if IKONOS satellite has been launched in last year, the 1m-resolution image data is not available to customers at this moment. So, we decided to simulate the 1m-resolution satellite image using 8.6 cm airborne image. The image was resampled in 1m and the MTF of satellite camera and the effect due to the satellite attitude were considered. The simulated image taken over down town area of Taejon, Korea is shown in figure 1.

Our method was applied to the simulated image and the quality of our method was visually assessed.

The results of our method are shown in figure 8, 9, 10 and 11.

4. Discussion and Conclusion

We proposed the knowledge-based approach to the road extraction from the 1m-resolution satellite images. The road extraction from the 1m-resolution satellite images differs from dealing with the airborne images or low-resolution satellite images. In low-resolution satellite images, the roads in urban area do not appear, and airborne images show features in detail so that many features can be incorporated to detect roads. However, in the 1m-resolution images, it does not show many details and furthermore, roads are not "line-like" objects. The final target of our project is to generate vector maps[2] from the 1m-resolution satellite images. To produce vector maps, we have to extract the centerline, and borderlines of roads should be extracted. In this paper, we proposed a method to identify the road regions. We are planning to develop a method to find those lines based on the original image and the detected road regions using the proposed algorithm. To search the borders of roads, the search areas should be defined and our proposed algorithm will be used to find the search areas.

As shown in the result image (Fig 11), some roads are missing and some falsely detected roads exist. This is usually because of the primary segmentation. This problem may be overcome by utilizing line information. As shown in figure 2 (line image), some lines that belong to road regions were extracted while our propose algorithm failed to detect the roads. Hence, the utilization of line information may improve the performance and this is remaining as future work.

[2] 1:5,000 to 1:10,000 scale - depending on horizontal accuracy of the satellite image and the horizontal accuracy depends on the satellite bus systems and the quality of geometric correction algorithm.

Acknowledgement

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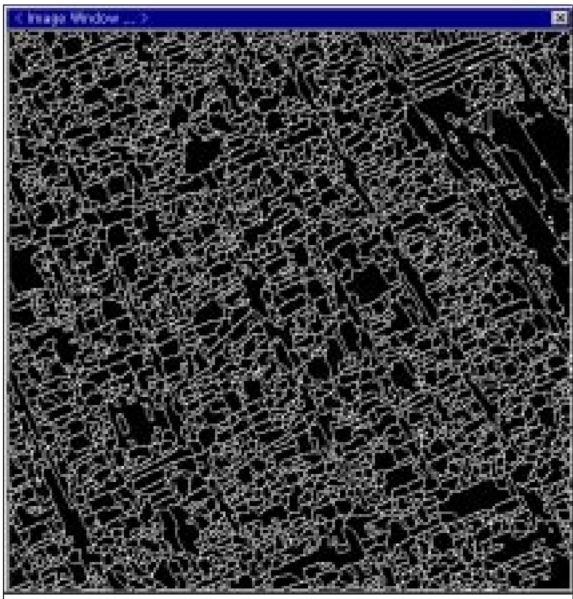

Figure 8. Watershed Segmented Image

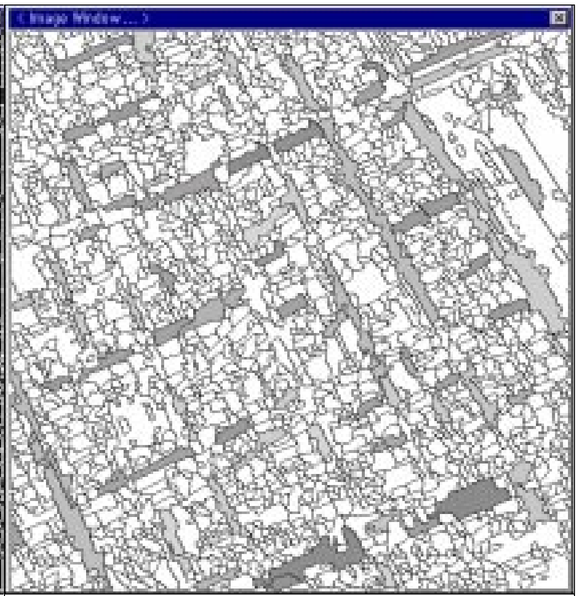

Figure 9. Road Candidate Image

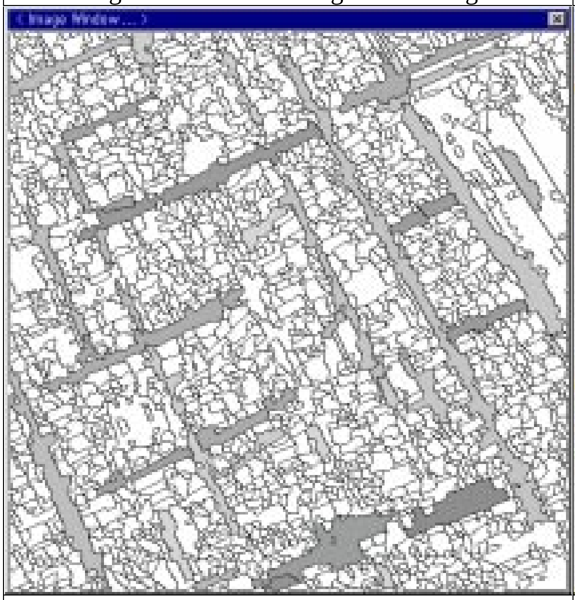

Figure 10. Road were reconnected.

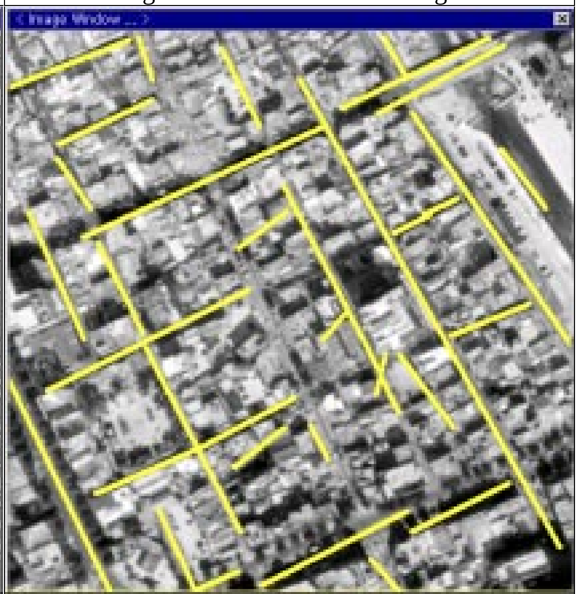

Figure 11. Detected roads