A Robust Method for Semi-Automatic Extraction of Road Centerlines Using a Piecewise Parabolic Model and Least Square Template Matching

Xiangyun Hu, Zuxun Zhang, and C. Vincent Tao

Abstract

In this paper, we present a semi-automatic road extraction method based on a piecewise parabola model with 0-order continuity. The piecewise parabola model is constructed by seed points coarsely placed by a human operator. In this case, road extraction actually becomes a physical problem of solving of each piece of parabola with only two or three unknown parameters by using image constraints. We have used a least square template matching to solve the parabola parameters. The template is deformable developed based on the automatic detection of dual road edges. In addition, a method of flexible observation weight evaluation has also been developed in this matching method. Extensive testing experiments on various image sets demonstrate that the method is able to extract road centerlines reliably. It offers much higher efficiency in contrast to manual digitizing process. We also discuss some issues about semiautomatic road extraction and future work for improving the reliability and extending the availability of our method.

Introduction

In the past decades, numerous methods in road extraction from spatial imagery (aerial and satellite) have been presented. There are many significant advances in the development of methods and algorithms for road extraction. Due to the complexity of the automation process, the human operator still plays a principle role in extracting road information from imagery.

The key issue in automatic object extraction is reliable object identification. In recent years the human machine cooperation strategy for object extraction has been an active research area. In this strategy, the object of interest is first identified by a human operator and some seed points are often provided, the object is then delineated automatically and accurately by the computer algorithm. This is also called semiautomatic extraction. The bottle-neck problem in identifying the object is thus eliminated, and the given approximations serve as strong constraints to control the extraction process, offering more reliable and accurate extraction result.

For the semi-automatic road extraction, there are basically two ways to provide the approximations. One is to give an initial point and an approximate direction for the subsequent automatic extraction. In Nevatia and Babu (1980), edge analysis is a key clue for road finding from some given seeds. The profile matching combined with the Kalman filtering algorithm is presented in Vosselman and de Knecht (1995). A road tracking system developed by Mckeown and Denlinger (1988) uses both edge clues and the profile matching techniques as a cooperative strategy for road extraction from aerial imagery. Tao (2000) used a multiple-image matching strategy for object measurement from mobile mapping image sequences of road corridors. In his method, an object point in one image is measured manually as the initial information. Couloigner and Ranchin (2000) presented a semi-automatic method of street extraction from the urban area. It makes use of a wavelet-based, multi-scale representation of the image. When a set of seed points are input as the approximation, the least square template matching method (Agouris, et al., 2000) and the differential snakes (Agouris, et al., 2001) are used for road extraction. From a viewpoint of practical operations, sequentially inputting the seed points for road extraction can be integrated with the manual digitizing process naturally. Gruen and Li (1995) presented a model-driven method which uses dynamic programming for road extraction. They also developed a method that is based on the snakes and the least square template matching (LSB-SNAKES). This method can be used to perform the high precision linear feature (for example, the road centerline) tracking in two-dimensional image space or three-dimensional object space (Gruen and Li, 1997; Li, 1997).

In this paper, we present a concise geometric representation of a road centerline, piecewise parabola with 0-order continuity, for semi-automatic road extraction. The objective of the method is to develop a robust and user friendly tool that can be integrated into a digitizing production with high reliability, efficiency, and accuracy.

Overall Strategy of Semi-Automatic Road Centerlines Extraction

The semi-automatic method attempts to integrate the intelligence of our human visual system with an ability to recognize the object robustly and the computer system with an ability to perform fast feature extraction and accurate shape representation. To ensure that the semi-automatic road extraction can be applied in a real operational environment, the method needs to guarantee better performance in terms of:

- Reliability: Extraction is not sensitive to the noise (shadows and occlusions) and the slight variation of position of the input approximations, i.e., re-doing or correcting (editing) of the extracted result should be largely minimized.

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Piecewise Parabola Extraction

Our method is based on a concise road geometric representation along with a deformable template matching method. More importantly, the method can be seamlessly integrated into a practical digitizing process. Figure 1 depicts the strategy and the workflow of the approach. After inputting the road width, in a local coordinate system, as shown in Figure 1b, the initial parabola in the first segment is extracted as model_0, and the consecutive parabola extracted as model_1. S_0, S_1, S_2, ... are the seed points. In the first segment (segment_0) the local coordinate system is built so as the x-axis is along the direction defined by seed point pair (S_0,S_1). In the subsequent segments it is built so as the x-axis is along the direction defined by the end point of the last piece of parabola (point O) and the current seed point (point S_i). The extracted road centreline is a piecewise parabola with 0-order continuity. It means the neighbour piece of parabolas have a common point in the junction. In the local coordinate system, a linear representation of the centerline is used. For the model_0,

\[ y = a_0 + a_1 x + a_2 x^2, \quad (1) \]

and for the model_1,

\[ y = 0 + a_1 x + a_2 x^2 = a_3 x + a_4 x^2. \quad (2) \]

In Equation 2, the parameter a_0 is 0 because we set the original point of the coordinate system in the end point of the last piece of parabola (here, \(x = 0\), and \(y = 0\), so \(a_0 = 0\)). When the coefficient \(a_2 = 0\), it is a piece of a straight line segment.

There are three reasons to use the piecewise parabolic description to control the entire semi-automatic road extraction: (a) By observing various spatial images (aerial and satellite images), we find that most road centrelines can be fitted as piecewise parabolas with 0-order continuity. The representation by Equations 1 and 2 can also easily delineate sharp turns and any straight pieces along the centrelines by setting \(a_2 = 0\), as shown in Figure 2. Use of a spline would be difficult to determine optimal knots to fit the curve in this situation (Li, 1997). (b) Essentially, as a human-machine cooperation strategy, it employs the human operator’s intelligence to coarsely delineate the piecewise parabola by sequential seed points; hence, it imposes strong constraints on the extraction through the definite and simple geometric model. Generally, combining the image feature together with the geometric constraints can serve as the so-called internal constraints for more reliable extraction. It has been used in the snakes-based method and has quite good results (Gruen and Li, 1997). In our method, in most cases only two parameters (\(a_1\) and \(a_2\)) need to be estimated. Even with heavy noises (i.e., occlusions), the geometric model controls the extraction to output reasonable results according to the description of the parabola. (c) Considering the factor of user friendly, extraction of piecewise parabola with 0-order continuity can be seamlessly integrated into the digitizing procedure. Traditionally, the full manual digitizing just records the points inputted sequentially (such as, \(S_0, S_1, S_2, \ldots\)), while our method automatically extracts pieces of parabolas with the inputting of the approximate seed points. Due to the piecewise

![Figure 1. A robust method of piecewise parabola extraction: (a) Work flow of piecewise parabola extraction, and (b) illustration of the piecewise parabola extraction.](image)

![Figure 2. Road centerline description by a piecewise parabola with 0-order continuity.](image)
parabola description, extraction in each segment defined by the seed point pair is relatively independent; so, when a wrong extraction result emerges, one can cancel the current extraction and re-do or correct it. The human operator inputs only a few seed points; other great numbers of intermediate points are produced by the algorithm. The extraction method is with timely feed back in the interactive extraction procedure, so it is naturally combined with the common digitizing procedure under the human operator’s supervision. However, when the dominant feature of the roads takes on the street grid, for example in dense urban areas, to delineate the sharp turns and orthogonal intersections, we need input quite a lot seed points to locate the sharp turns which results in a drawback in efficiency.

The computation of the parabola parameters is realized by the least square template matching. With the deformable template and the constraint of the geometric model, the algorithm extracts each piece of the parabola reliably and accurately.

**Parabola Extraction Using Least Square Template Matching with Deformable Template Generation**

Least square template matching is derived from least square image matching, which can be used for precisely reconstructing object surface (Heipke, 1992) and high accuracy dimensional measurement (Gruen and Stallmann, 1992). The least square template matching has great advantages in integrating internal (geometric) and external (image features) constraints. It has the rigorous theory and methods for quality control and result assessment (Li, 1997), and has been successfully used in semi-automatic linear feature extraction (Gruen and Agouris, 1994; Gruen and Li, 1997). Based on the dual edge feature of the road, we make use of least square template matching as the primary algorithm to solve the parameters of the parabola to be extracted.

Our method is illustrated in Figure 3. In Figure 3a, a local coordinate system x-O-y is built as mentioned before, where O is the end point of the last parabola and S is the seed point. The initial centerline $c_0$ is OS ($y = 0 \cdot x + 0 \cdot x^2$), and its dual edges are $e_1$ and $e_2$. The actual centerline is $c (y = a_1 x + a_2 x^2$), its dual edges are $E_1$ and $E_2$. Using least square template matching the error between $c_0$ and $c (\Delta y = \Delta a_1 x + \Delta a_2 x^2)$ can be estimated by the errors in the $y$ direction (i.e., in position $x_k$). Let $g_{mn}$ is a gray value of the template which represents the gray pattern of the road, $g$ is an observation value of the pixel gray in the current feature position,

$$g_m = g(y + dy) = g + \frac{dg}{dy} \Delta y. \quad (3)$$

Combining Equation 3 with the parabola representation $y = a_1 x + a_2 x^2$ and $\Delta y = \Delta a_1 x + \Delta a_2 x^2$, there is an error equation:

$$g'_c x_k \Delta a_1 + g'_c x_k^2 \Delta a_2 - (g_m - g) = v_g \quad p. \quad (4)$$

Here $g'_c$ is the gray gradient in the $y$ direction ($g'_c = g(x_k, y) - g(x_k, y - 1)$), and $p$ is the weight of the observation. This is the computational model of error adjustment to estimate the parabola parameters. It is an iterative processing for adjusting initial parameters to fit the actual centerline, which is defined by the templates and the imposed geometric model. The initial parameters $a_1$ and $a_2$ are 0 respectively, and then they are corrected iteratively.

The templates serve as the standard gray pattern that attracts the initial parabola to the final version, so it is very important to develop the appropriate templates. Figure 3b shows the generation of the deformable templates. To generate a template, first a dual, step-edge finder is applied to detect local maximums of the edge intensity:

$$g'_c max = \max(\max([g'_c x_k]) + \max([g'_c x_{k-1}]), g'_c x_{k+1}, k=0, 1, \ldots, 25). \quad (5)$$

Max($g'_c x_k$) and Max($g'_c x_{k-1}$) are respectively the local maximum of gradient magnitude whose location is close to initial edge position. They are evaluated in a small search range (i.e., five pixels along $y$ direction). We assume that dual edges of the roadside are in the reverse directions. The road width defined by the detected dual edges is not constant, and the corresponding step-edge template is generated by $\max([g'_c x_k])$ and $\max([g'_c x_{k-1}]).$ Here a $5 \times 5$ template is used. In the template the step-edge pattern is represented by setting the edge intensity identical to the detected gradient maximum. Using a dual, step-edge finder, deformable road templates are self-adaptive to the slight change of road width and the varying of the dual edge intensities. Finally, numerous observations are employed to solve the two parameters of the parabola.

The weight $p$ is set according to the local maximum of gradient magnitude and the curvature of current point in observation. Figure 4 shows the definition of the curvature. The curvature measure depends on relative direction of neighbor vectors (Williams and Shah, 1992),

$$\text{Curv}_k = \frac{\bar{u}_k - \bar{u}_{k+1}}{\bar{u}_k x_{k+1} - \bar{u}_k x_{k+1}} \quad (6)$$

where $\bar{u}_k = (x_k - x_{k-1}, y_k - y_{k-1}), \bar{u}_{k+1} = (x_{k+1} - x_k, y_{k+1} - y_k), \bar{u}_{k+1} = (x_{k+1} - x_k, y_{k+1} - y_k)$. The weight is

$$p = \frac{\text{Max}([g'_c x_k])}{128} + (5.0 - \text{Curv}_k). \quad (7)$$

Figure 4. Curvature of a local observation.
This means that the observation with high edge intensity and small curvature, plays dominant role in the adjustment processing. These constraints imposed on the computational model are used for maximizing the extraction reliability and accuracy. Figure 5 displays an extraction result where parts of the road are covered by trees and their shadows. The dots and black lines represent seed points and the extracted road centerline, respectively. Under all constraints used, the algorithm produces a reasonable result. It automatically inserts some intermediate points between each pair of consecutive seeds to delineate the parabolas. The result is similar to the full manual digitizing result conducted by a human operator.

As the algorithm for solving the parabola parameters heavily depends on the radiometric feature of dual edges, there will be a drawback when the edges are very unclear. One often seen case is in multi-spectral images where there are usually apparent spectral differences between the roads and the background, while the radiometric contrasts are very weak. It will lead to unreliable results by the algorithm, therefore spectral information should be taken into account.

Experiments
We developed a testing platform based on the above method. Seed points are input through the interface by clicking the mouse. We attempt to evaluate how fast (efficiency) and how reliable is defined by counting the number of re-doing or correcting the wrongly extracted parabola. The successful rate is defined by

\[ R = 1.0 - \frac{N_r}{N_p}, \]  

Here \( N_r \) is the total amount of the seed points, and \( N_p \) is the total number of re-doing or correcting during the extraction procedure.

Many aerial and satellite images of different ground resolutions have been tested. Figure 6 shows an aerial photograph and a Quickbird image with 0.7 m resolution. Each of them covers a large rural or urban area and contains lots of road types. In Figure 6a, roads are in rural areas where trees and residential areas often obscure the paved roads, and most of the roads are linear, thin, and bright features. Figure 6b is a high-resolution satellite image containing hybrid areas including dense urban and suburban areas, where the roads are more likely ribbon features. At the beginning of extraction for each road, the road width needs to be measured manually. To control the extraction procedure, the human operator plays a role in determining whether it is necessary to re-do or correct some pieces of the parabolas during the interactive extraction procedure. Some results on the images are displayed in Figure 7.

Figure 5. Extraction under noises.

Figure 6. Testing images: (a) Aerial photograph, Ground resolution = 1.47 m/pixel, image size = 9021 \times 9086, and (b) Quickbird image, Ground resolution = 0.7 m/pixel, image size = 13377 \times 16423.

Figure 6a. The extracted piecewise parabola is still reasonable and accurate even the noises and road width varying existing. In Figure 7b, a patch of extraction result from an urban area in the Quickbird image is shown. The black dots and white lines are input seed points and extracted road centerlines, respectively. Even under the complex image environment and with varying road textures, the method can extract the road centerlines successfully.

Table 1 shows the statistical result on testing the efficiency and reliability of the semi-automatic road extraction method. Compared to the full manual digitizing (that means the measurement of precise position of road centerlines is fully fulfilled by a human operator), our method has a higher efficiency, at least two times. In rural areas, the successful rate \( R \) is 0.96 and in urban area \( R \) is 0.94. It means that when 100 seed points are input, only 2 to 6 pieces of parabolas need a re-do or corrections. In the tests, accuracy is only judged by the human operator with a comparison to the manual results. The experiments indicate a great potential of the developed method for practical production for GIS data collection.

Conclusions and Future Work
We presented a semi-automatic extraction method of road centerlines based on a piecewise parabolic geometric model along with a least squares template matching. The geometric model is constructed by the seed points placed by a human operator. The method can delineate road centerlines robustly and efficiently, including centerlines with sharp turns. On the other hand, it is a user-friendly method as it is integrated into a normal digitizing process seamlessly. It permits the human operator to perform correction of wrongly extracted results immediately and interactively. The reliability is improved by using a least square template matching with deformable road templates along with a flexible observation weighting scheme. Extensive testing experiments on various images indicate the method is able to extract road centerlines very efficiently (at least two times) in contrast to the manual digitizing.

Although the method is successfully applied for digitizing roads from the images in which the roads take on features of dual edges in radiometry, there are still some drawbacks which indicate our feature work be extended and improve the method:

- The geometric model of piecewise parabola is constructed initially by a human operator, improper placement of the seed points (for example, trying to extract a much curved line by giving only two sequential seeds) will lead to unsatisfactory or wrong results. One solution to this problem is to readjust...
Figure 7. Semiautomatic road centerlines extraction from spatial images: (a) Extraction from the aerial image (rural area), and (b) Extraction from the high resolution Quickbird satellite image (urban area).

<table>
<thead>
<tr>
<th></th>
<th>Manual (image a)</th>
<th>Manual (image b)</th>
<th>Semi-Automatic (image a)</th>
<th>Semi-Automatic (image b)</th>
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<tr>
<td>Time (minute + second)</td>
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<td>34 m + 13 s</td>
<td>5 m + 40 s</td>
<td>12 m + 25 s</td>
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<tr>
<td>Total road length (km)</td>
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<td>180.33 km</td>
<td>86.14 km</td>
<td>166.47 km</td>
</tr>
<tr>
<td>Number of seed points or parabola pieces</td>
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<td>1570</td>
<td>445</td>
<td>848</td>
</tr>
<tr>
<td>Successful rate $R$</td>
<td>/</td>
<td>/</td>
<td>0.98</td>
<td>0.94</td>
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the seed points adaptively based on pre-matching of the model and image. In the densely populated areas, generally roads have sharp turns and orthogonal intersections, so that the parabolic model is not suitable when the two sequential seed points are placed to extract a sharp turn or intersection. One has to carefully input the seed points indicating the sharp turn locations (refer to Figure 2). This will be a drawback in efficiency. To deal with this, we need to develop a piecewise and higher order description of the roads. It will also help in extraction of the more curved roads in small scale images.

- The solution of the parabola parameters depends on the radiometric features and intensity edges. It limits the application of the algorithm in cases of complicated road textures and lack of dual edge features, especially in the multi-spectral images in which different roads have different spectral response while their radiometric features could be too weak to be used for extraction. The spectral information from different bands and the more complicated road texture model should be taken into account. The key problems are to correctly generate the templates and to fuse different spectral features from the multi-bands.

References


