An Integrated Approach of Automatic Road Extraction and Evaluation From Remotely Sensed Imagery

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Abstract

This paper proposed an integrated approach for automatic road extraction from remotely sensed imagery by combining digital image processing, remote sensing and geographic information system (GIS) technologies. Roads are modeled as continuous single lines with bar-shaped or parabolic-shaped profiles in the direction perpendicular to the road. The roads are extracted based on differential geometric properties. Then, further GIS operations are processed to get vector roads with better cartographic quality. Landsat7 ETM+ data with 30 meters resolution, 1 meter USGS DOQ (Digital Ortho Quad), 1 meter IKONOS image and 0.25 meter scanned aerial photograph are used to test this approach. The results are evaluated by comparing to manually acquired road data. Several quality measures (Completeness, Correctness, Quality etc.) are used for accuracy assessment. The results show that this approach can extract more than 90% roads if the contrast is sufficient. A set of algorithms has been successfully developed in a GIS environment. The integration of GIS and remote sensing technologies provides a promising approach for GIS data collecting and updating.

Introduction

Today satellite and airborne remote sensing systems can provide large volumes of data that is invaluable in monitoring the Earth resources and the effects of human activities on the Earth. However, from mapping perspective, researches in remote sensing are mostly focused on land use / land cover classification. Few individuals are involved in the research of cultural feature extraction, i.e. the detection, identification, classification, and delineation of man-made features. In recent years, remarkable progress has been achieved in digital (softcopy) photogrammetry. Now, digital elevation models (DEM) and digital orthophotographs can be automatically generated. However, the tasks of feature identification and cartographic delineation are primarily still done manually. These tasks are time consuming, very labor intensive and costly.

Innumerable public agencies and private companies require the most current and complete digital cartographic information available. Typically map products cannot maintain currency because of the rapid pace of development. Remote sensing systems can provide current raw data in image format to update the GIS databases. Therefore there is an urgent requirement to develop automatic, fast and reliable approaches to extract cartographic information from remotely sensed imagery. Actually, automatic feature extraction from remotely sensed imagery has especially important application of map creation for many developing countries or rural areas in some developed countries. In these areas, there are often no up to date maps or even no maps at all.

This paper focuses on the automatic road extraction from multi-resolution imagery. A set of algorithms for road extraction was developed within the ESRI (Environmental Systems Research Institute, Inc.) GIS environment. Roads are modeled as single centerlines with contrasting background. Several multi-resolution images, i.e. 30 meters Landsat7 ETM+, 1 meter IKONOS image, 1 meter digital DOQ, and 0.25 meter aerial photograph were tested. Several quality measures were used to conduct accuracy assessment by comparing the extracted roads with manually acquired reference roads.

The next section presents an overview of the automatic and semi-automatic approaches for road extraction. The road model and methodology are presented in the following section. The results and accuracy assessment are illustrated next. Finally some conclusions and suggestions for improvement are discussed.

Related Research

Automatic road extraction approaches can be classified into two general categories: semi-automatic and fully automatic. The semi-automatic approaches require extensive human interactions, while fully automatic methods do not.

For road extraction in low-resolution imagery, the most common automatic techniques are detecting and tracking lines. For road extraction in high-resolution imagery, roads are considered as elongated homogeneous regions and are often detected by matching profiles and parallel edges (Baumgartner et al. 1999).

An early approach proposed by Fischer et al. (1981) combined local road evidence obtained from multiple line detectors and tracked the road by finding a minimum cost path. Steger (1996) developed a more sophisticated approach based on differential geometry. First the derivatives of image function are estimated by convolving with derivatives of a Gaussian kernel. Then, roads were extracted from the second derivative image using a hysteresis threshold technique.

Baumgartner et al. (1997, 1999) presented a multi-resolution approach. Lines are extracted using the algorithm of Steger (1996) in a reduced-resolution image and edges are extracted from the original high-resolution aerial photograph. After fusing the results, short road segments are grouped into longer segments by closing the gaps based on geometric and radiometric criteria. Similarly, Wang and Trinder (1998) proposed an approach based on road network topology.

Most approaches of road extraction use panchromatic images only. Wiedemann et al. (1998) made use of multi-spectral information for road extraction from MOMS-2P (Modular Optoelectronic Multi-spectral Scanner) image.

Many other techniques can also be used to extract roads. Lin et al. (2000) combined generalized constrained energy minimization with a principal component analysis-based fusion technique to extract urban roads. Cao and Qin (1998) combined image processing with artificial intelligence methodologies to develop a road detection technique based on shape index and other priori knowledge. Solaiman et al. (1998) applied fuzzy concepts to extract road from a SPOT image. Learning vector quantization was used by Brown and Marin (1995). Tupin et al. (1998) identified roads by defining a Markov Random Field (MRF) introducing contextual knowledge about road object shape in Synthetic Aperture Radar (SAR) images.

Maps, GIS data or other ancillary data can be used to facilitate road extraction. Cleynenbreugel et al. (1990) used an object-oriented expert system to extract roads from SPOT imagery. They used land-cover information to aid in the delineating of forest path networks and used a DEM to aid delineation of mountain roads. Gunst and Vosselman (1997) constructed knowledge-based semantic models for interpretation of road networks in aerial images. Fiset and Cavayas (1997) tested a map-guided procedure combined with a back-propagation neural network. Jeon et al. (1999) presented a map-based road detection algorithm from space borne SAR images.

METHODOLOGY

Road Model

A road is a long, narrow stretch with a smoothed or paved surface, made for traveling by motor vehicle, carriage etc (Flexner, 1993). However, this is a very general definition. Vosselman and Knecht (1995) provided a more detailed description of road characteristics. They categorized road components into five groups: geometrical, radiometrical, topological, functional and contextual. These characteristics describe some features that are used by a human operator to recognize and map roads. Roads on digital imagery are continuous and narrow regions that are lighter or darker than regions on either side. Also, the gray values (spectral reflectance) along a road usually do not change much within short distances.

In this research, we model roads as linear features within grayscale image. The image is regarded as a function and roads have bar-shaped or parabolically shaped grayscale profiles in the direction perpendicular to the roads.

Automated Road Extraction Scheme

Figure 1 outlines the scheme of road extraction process. There are three basic procedures: image preprocessing, road extracting and GIS processing.

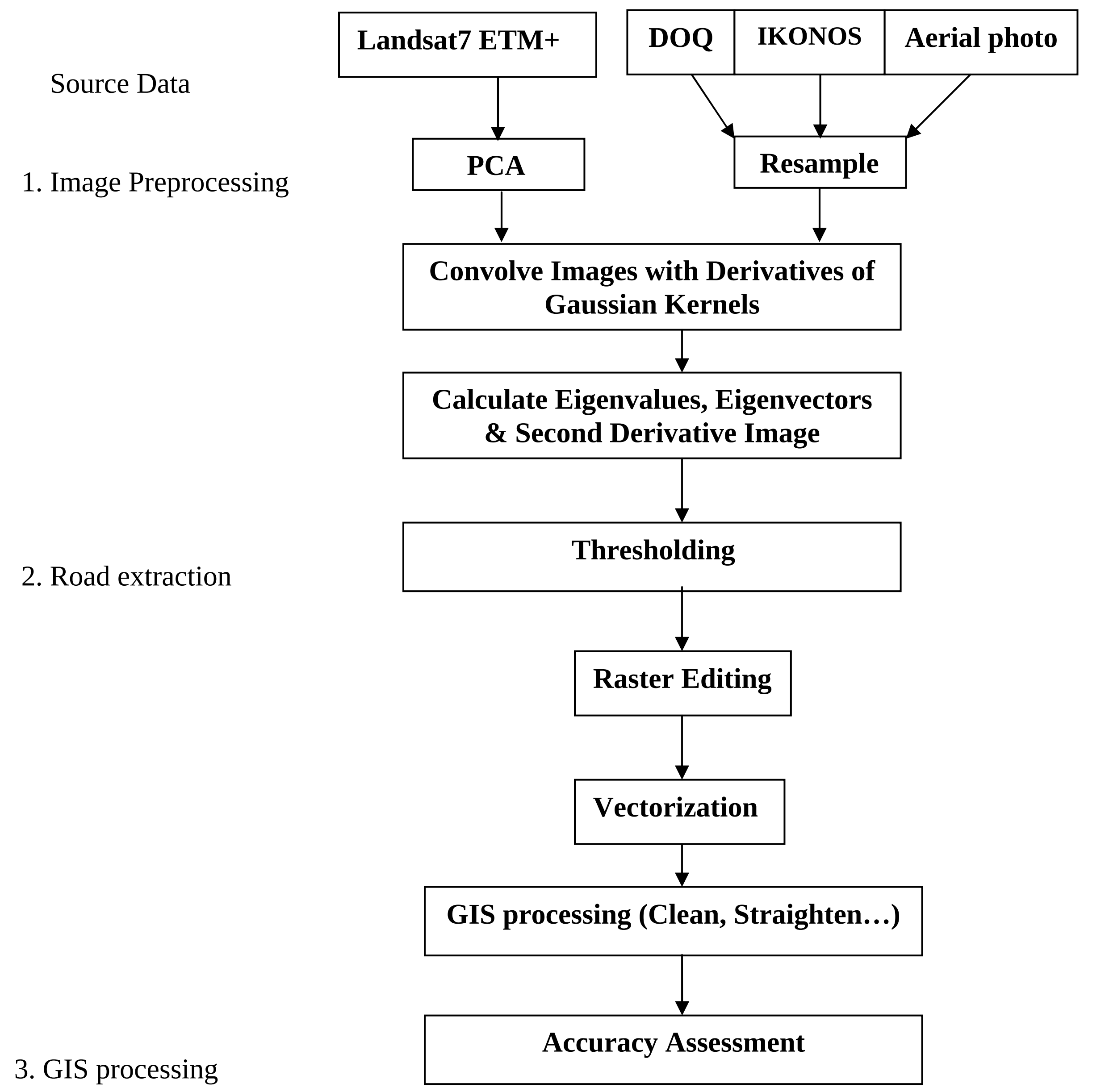

Figure 1. A Road Extraction Scheme

1. Image Preprocessing

Principle Components Analysis

The original Landsat7 ETM+ image has six reflective bands. While any one of these bands could be used, the contrast between the roads and their background is not ideal. Some image enhancement processing is needed. Principal components analysis (PCA) uses a linear transformation of the multi-band data to translate and rotate data into a new coordinate system that maximizes the variance of the data. The transformation of the raw data using PCA can result in new principle component images that may be more interpretable than the original data (Jensen, 1996). Visual comparison showed that roads in the second principal component (PC2) have the best contrast among all components. This PC2 image is used for further road extraction.

Resampling

Within this research, we are only interested in extracting single road centerlines. The U.S.G.S. DOQ and IKONOS images have 1 meter resolution while the scanned aerial photograph has 0.25 meter resolution. To utilize our algorithm, these original images are resampled to cause the roads to become a few pixels wide. Then, from these reduced resolution images, the road centerlines can be extracted using the road extraction algorithms described in the next section.

2. Road Extraction

Normally roads are linear features with contrasting background. Therefore, road points have a local minimum or maximum grayscale value along the direction perpendicular to road. At these locations, the first directional derivative should vanish, and the second derivative will have a large absolute value. The first and second derivatives of the image function can be estimated by convolving the image with the first and second derivatives of a Gaussian kernel (Steger, 1996).

The roads in 2-D can be modeled as curves that exhibit characteristics of the 1-D road profile. The direction perpendicular to the roads can be assumed to be the direction in which the second directional derivative achieves extreme value. This can be obtained through the Hessian matrix that is constructed using the second partial derivatives of the image. By calculating the eigenvector corresponding to the largest absolute eigenvalue of the Hessian matrix, we can obtain the direction perpendicular to the road.

A binary road image is obtained by thesholding the second derivative image using an appropriate value. User can derive roads of different width using multiple parameters separately.

3. GIS processing

The primary results of road extraction are usually fragmented. Further GIS processing is needed to remove noise and achieve better cartographic results.

Raster Editing

Two automated raster-editing tools are used to remove noise. One technique removes speckle noise, or small clusters of cells that can be contained by a specified box. The other removes regions of connected cells whose total cell number fall within a given range. By setting an appropriate threshold, speckles and small regions can be removed. Other techniques such as spatial smoothing filter may also be helpful in removing noise.

Vector processing

After raster editing, a raster-to-vector conversion transforms the binary road image into vector lines. Then a 'CLEAN' operation is performed to create topology and correct geometric coordinate errors automatically. By setting a minimum length allowed for dangling arcs, any dangling arc segments shorter than the specified length are deleted.

The vector lines produced from a raster-to-vector conversion may still have some problems even after the CLEAN operation. One is the occurrence of dimpled intersections caused by raster-to-vector conversion. A straighten operation is performed to remove the dimpled part of the intersection. This creates lines with more satisfactory intersections.

The raster-to-vector conversion also causes vector lines having zigzag shape resulting from the fact that the input was a cell-based image. A generalization operation is run to remove these extraneous bends and small intrusions and extrusions from the line without destroying or significantly modifying its essential shape. The results of these operations have better cartographic quality after eliminating redundant details.

Results & Assessment

Many factors such as resolution or context play important role in determining the result of road extraction. Therefore, multi-resolution sub-images (30 meters Landsat7 ETM+, 1 meter IKONOS, 1 meter DOQ, and 0.25 meter aerial photograph) within forest, rural, suburban, residential, and urban areas were used to test the robustness and adaptability of the developed algorithms.

The automatically extracted roads are compared with manually digitized reference roads to perform accuracy assessment. Because roads are linear features, it is possible to use all the data rather than just sample points to conduct the accuracy assessment in a GIS environment. Heipke et al. (1997) proposed several quality measures to evaluate the quality of extracted roads. Federal Geographic Data Committee (FGDC) defined standard to estimate positional accuracy using root-mean-square error (FGDC, 1998). We use the following measures for accuracy assessment of road extraction:

- $$\textbf{Completeness} = \frac{\textbf{Length of matched extraction}}{\textbf{Length of reference}} \qquad (1)$$

- $$\textbf{Correctness} = \frac{\textbf{Length of matched extraction}}{\textbf{Length of extraction}} \quad (2)$$
- $$\textbf{Quality} = \frac{\textbf{Length of matched extraction}}{\textbf{Length of extraction} + \textbf{Length of unmatched reference}} \quad (3)$$
- $$\textbf{RMSE} = \sqrt{\sum[(x_{extrcted} - x_{reference})^2 + (y_{extracted} - y_{reference})^2]/n} \quad (4)$$
- **Horizontal Accuracy = 1.7308 * RMS (Root Mean Square)** (5)

Completeness represents the percentage of reference data being correctly extracted. Correctness indicates the percentage of correctly extracted roads. Therefore, completeness is producer's accuracy and Correctness is users' accuracy. The quality represents the overall accuracy and the RMSE (Root Mean Square error) expresses the geometrical accuracy of extracted roads.

To calculate these quality measures, buffer zones are generated around the extracted roads and the reference roads. The chosen buffer width is approximately half of the actual road width. Then, by using GIS overlay analysis, matched extraction roads are derived by intersecting the extracted roads with the buffer zone of reference. Matched reference roads are derived by intersecting reference with the buffer zone of extracted roads. Therefore, we can obtain the completeness, correctness and quality measures. Also the RMS error and horizontal accuracy measure can be obtained by calculating the distance between extracted road points and reference roads.

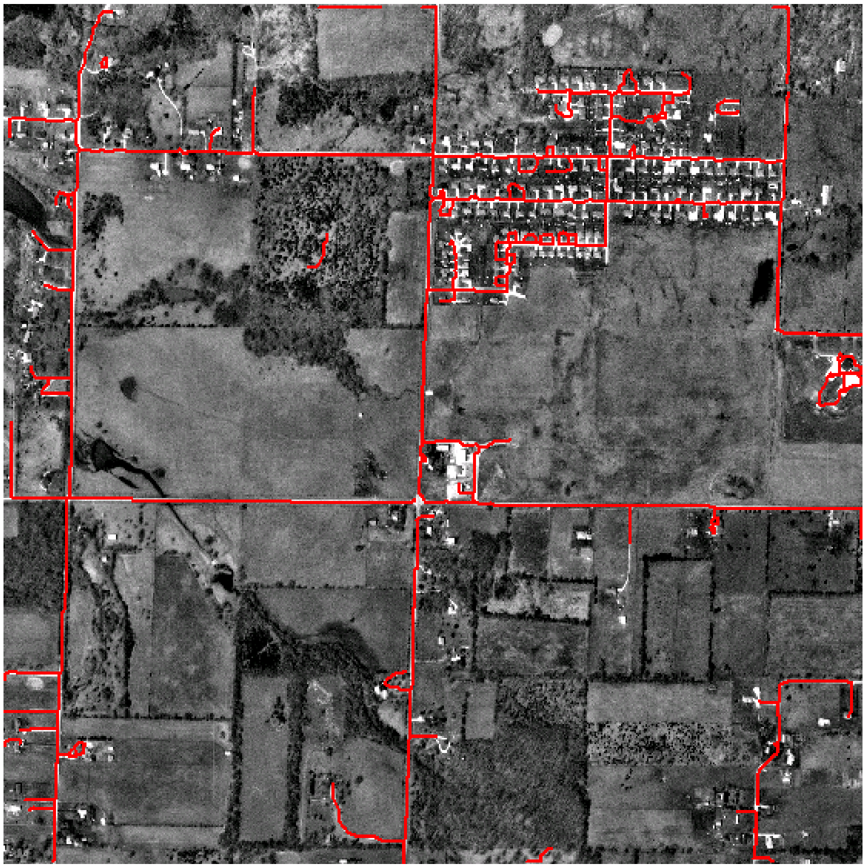

Figure 2. Extracted roads (red) from a DOQ image

Table1. Accuracy Assessment for DOQ

	Extracted Road	Reference
Matched	11725.30	11504.15
Unmatched	5945.92	822.30
Total Length (m)	17671.22	12326.45
Buffer Distance (m)	3.5	
Completeness	95%	
Correctness	66%	
Quality	63%	
RMSE (m)	2.00	
Accuracy (m)	3.46	

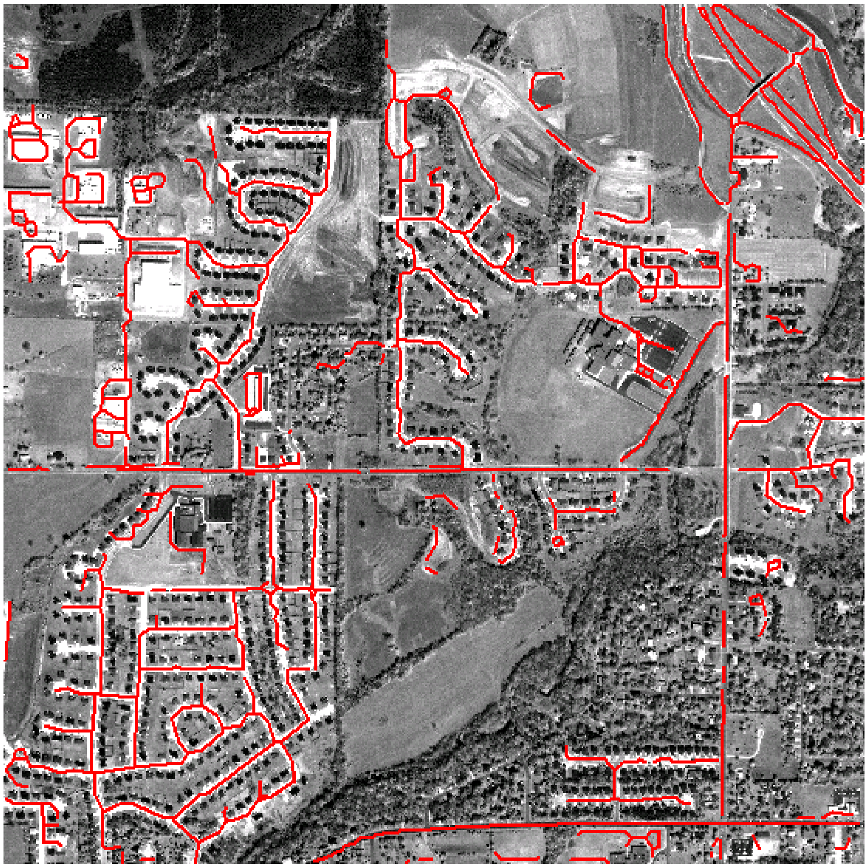

Figure 3. Extracted roads (red) from IKONOS image

Table 2. Accuracy Assessment for IKONOS

	Extracted Road	Reference
Matched	21548.00	21302.37
Unmatched	10854.50	4695.57
Total Length (m)	32402.50	25997.94
Buffer Distance (m)	7	
Completeness	83%	
Correctness	66%	
Quality	58%	
RMSE (m)	3.08	
Accuracy (m)	5.33	

Figure 2 shows the road extraction results from a suburban DOQ image. The completeness is 95% and correctness is 66%. That means 95% of the roads were successfully extracted and 66% of extracted road were correct. The main cause of low correctness is extraction of driveways. Driveways usually are not collected in most GIS database. However, the extraction of driveways may be useful for certain agencies such as fire departments.

Figure 3 and table 2 show the results from IKONOS image of a residential area. 83% roads were extracted and 66% were correct. Shadows and bad contrast contribute to un-extracted roads and lead to low completeness. Building roofs or other objects with similar reflective value cause low correctness.

Conclusion

An integrated approach for automatic road extraction from remotely sensed imagery is successfully developed combining digital image processing, remote sensing and geographic information system technologies. This approach is based on differential geometry. Roads are modeled as continuous single lines with bar-shaped or parabolic-shaped profiles. Roads are extracted from the second derivative image and refined with GIS operations. All the algorithms are developed and integrated in a GIS environment.

Four kinds of commonly used remote sensing data i.e. 30 meters Landsat7 ETM+, 1 meter IKONOS, 1 meter DOQ, and 0.25 meter aerial photograph are used to test this approach. Several sub-images with forest, rural, suburban, residential and urban context are used. The accuracy assessments for these nine tested images show that our approach did a very good job. The average completeness is more than 80%. For rural and suburban areas, the completeness is greater than 90%. The results prove that our approach is excellent for extracting roads from images with good contrast. The approach efficiently integrates digital image processing, remote sensing and GIS technologies. It has great potential for updating old GIS data and commercial value.

There are still some problems with the automatic extraction of overclouded roads, which is the main reason for errors in road extraction. It is possible to use a snake technique to bridge shadowed parts of roads. Driveways are useful detailed information for some agencies. Understanding how to separate driveways from other roads is an area of future studies. Another factor influencing the correctness is building roofs. Additional data such digital surface model (DSM) can be used to remove the extracted building roofs. In urban area, the roads are often too complex for automated extraction. A more complicated road model needs to be constructed.

Automatic road extraction from remotely sensed imagery saves a lot of time and money for GIS data collecting and updating. We will improve our approach and software, and make it being useful in practice for remote sensing and GIS communities.

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