Toward a system for road network automatic extraction in land consolidation using high spatial resolution imagery

Rui Guo[1, 2], Ming Luo[3], Wei Su[1], Daoliang Li [1, 2]*, Yijun Jiang[3], Zhengshan Ju[3], Jun Wang[3]
1. College of Information and Electrical Engineering, China Agricultural University,
17 Tsinghua East Road, Beijing 100083, China;
2. Key Laboratory of Modern Precision Agriculture System Integration, Ministry of Education, P.O. Box 209, Beijing, 100083, P.R. China
3. Land Consolidation and Rehabilitation Center, the Ministry of land Resources, Beijing 100035, China
* Corresponding Author: Email Address: li_daoliang@yahoo.com or dliangl@cau.edu.cn,
Tel: 86-10-62736717; Fax: 86-10-62736717.

Abstract: - Land consolidation is a tool for increasing the area of the arable land and improving the effectiveness of land cultivation. This paper presents a practical system for automatic road extraction in land consolidation to monitor the implementation of the project. The system integrates processing of color image data and information from digital spatial databases, takes into account context information, employs existing knowledge including plans of land consolidation, rules and models, and treats each road subclass accordingly. The system was designed as three-tier construction including interface, modules and database. The prototype system has been implemented as a stand-alone software package, and has been tested on a large number of images in different land consolidation areas. The parallel line segments are firstly detected and then the improved Active Contour Models (Snakes) are introduced to link the extracted road segments to the whole networks. The system was pilot used in the study area of Fangshan in Beijing which achieved satisfactory results.

Key-Words: - system, road extraction, land consolidation, high spatial resolution imagery, Snakes

1 Introduction

Land consolidation is a tool for improving the effectiveness of land cultivation, land productivity and also the total factor productivity if it induces and enhances technical progress and increases scale economies. Consolidation deals with a large number of phenomena, such as fields, roads, and land use, all of which exhibit characteristic forms and patterns which can be analyzed as to their existing spatial organization, or as to their changing spatial organization through time [1].

The linear feature to be extracted in a land consolidation project mainly contains roads, drains and pipelines. In a traditional way, people have to survey in the study area manually to acquire the accurate changes of roads after the project which could cost a lot. With the development of high resolution imagery and the improved feature extraction method, remote sensing has become an effective means of land use monitoring.

The existing road extraction approaches cover a wide variety of strategies, using different resolution aerial or satellite images. The approaches are generally classified according to the degree of automation: automatic method and semi-automatic method. Semi-automatic systems assisted by an operator seem to be more effective for road extraction now. However, the development trend of road extraction is automatic extraction system in the near future. After extracting the road network, there may be a few wrong results, which can also be corrected by the system operator.

Automatic methods usually extract reliable hypotheses for road segments through edge and line detection and then establish connections between road segments to form road network [2].

Hinz *et al.* [3] integrate detailed knowledge about roads and their context using explicitly formulated scale-dependent models. The knowledge about how and when certain parts of the road and context model are optimally exploited is expressed by an extraction strategy.

Mokhtarzade *et al.* [4] treats the possibility of using artificial neural networks for road detection from high-resolution satellite images on a part of RGB IKONOS and Quick-Bird images from Kish Island and Bushehr Harbor, respectively. Attempts are also made to verify the impacts of different input parameters on network's ability to find out optimum input vector for the problem. A variety of network structures with different iteration times are used to determine the best network structure and termination condition in training stage.

Laptev *et al.* [5] proposed a new approach for automatic road extraction from aerial imagery with a model and a strategy mainly based on the multi-scale detection of roads in combination with geometry-constrained edge extraction using snakes. It allows for the first time a bridging of shadows and partially occluded areas using the heavily disturbed evidence in the image.

Road extraction scheme presented by Trinder *et al*. [6] is based on Marr's theory of vision, which consists of low-level image processing for edge detection and linking, mid-level processing for the formation of road structure, and high-level processing for the recognition of roads. It uses a combined control strategy in which hypotheses are generated in a bottom-up mode and a top-down process is applied to predict the missing road segments.

Semi-automatic methods require operator to provide some information to control the extraction interactively.

Most semi-automatic approaches search for an optimal path between a few given points. Gruen and Li *et al*. [7] and Merlet *et al*. [8] connect points using dynamic programming, model-driven linear feature extraction algorithm based on dynamic programming. Gruen *et al*. [9] developed linear feature extraction method using dynamic programming and LSB-Snakes. They combined characteristics of snakes and Adaptive Least Squares Correlation method. This method might need large computation time on high-resolution images because of its linear systems.

Park and Kim [10] presented a road extraction algorithm using template matching. But the limitation is that it requires initial seed points on the road central lines and each road segment requires separate seed points. Shukla 's scheme is based on the cost minimization technique [11]. The cost is estimated by taking various factors into consideration such as variance, direction, length and width of the road. The process starts with the selection of seed points provided by the user. The approach is called as path following as it follows the path having minimum cost repetitively. Thus the path having minimum cost will be considered as a part of the road. Dal Poz *et al*. [12] presented a dynamic programming approach for semi-automated road extraction from medium- and high-resolution images, proposing a modification of merit function of the original dynamic programming approach, which is carried out by a constraint function embedding road edge properties.

Zhang *et al*. [13, 14] presented a practical system for automatic extraction of 3-D roads from stereo aerial images that integrate processing of color image data and existing digital spatial databases. Ohlhof *et al*. [15] presented an operational software system for the semi-automatic extraction of line and area features in 2D and 3D from aerial images and high resolution satellite imagery. The complete system was delivered to the Geo-Information Office of the German Federal Armed Forces and has been in practical use since May 2003 for the update of VMap Level 1 vector data and the generation of the military basic vector database.

The aim of this paper is to develop a support system for road network extraction in land consolidation area, enabling the manager to use quantitative and qualitative criteria in order to visualize the change of road network. The paper begins with a brief overview of characteristics of the study area. After that, the road model is illustrated. This is followed by an overview of the software architecture of the extraction system and its components, in which some implementation issues are mentioned. In the next section, the data base and the extraction workflows are described. Results achieved with high resolution satellite imagery and orthophotos are depicted. Finally, conclusions are drawn.

2 System architecture and implementation

The diagram in Fig. 1 represents the principal content of the developed system, which is composed of interface, modules and database.

The interface provides the user visible tools and data progressing tools, which can progresses the input data including the high resolution images and the plans of land consolidation. GIS tools are used as an important component of the system for capturing, storing, checking, manipulating data that are spatially referenced, transforming the extracted results to vector files and showing the changes of road network in different colours on the view.

The modules contain image progressing tools, programming language and road network extraction models, which extract the road network from the images within the land consolidation area. Further software modules, e.g. for the extraction of topographic or evaluation of land consolidation project, can be easily added, if required.

The last part is database which is the groundwork of the system. For the development of this case study, a geo-referenced database is built including high resolution images, plans of land consolidation, and maps of situation of land utilization. Depending on these, the system function can come true.

In order to develop the system, the Titan software tools have been used, considering cells of 2.5m^2 (the resolution associated with SPOT5 satellite image Data and metadata), which was imported to the spatial database as thematic data.

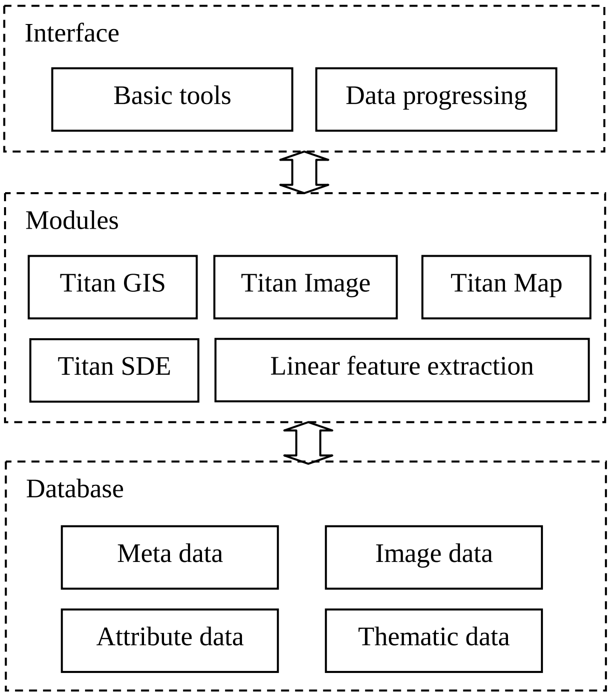


Fig.1 The system architecture

Titan tools are powerful and easy-to-use software in China. They give user the power to visualize, analyze, explore, query and progressing data spatially. Titan Map ActiveX (Tmapx) is a set of tools and mapping objects which allow the user to add maps in his application and to manage the map with the linked data base. Map Object applications can be greatly expanded when advanced programming is involved, such as Visual C++, Delphi and C#. Visual C++ is a powerful programming language, especially when it is used under Windows, Tmapx customized with Visual C++, allows user to construct various scenarios or proposals which can then be collected, combined, discussed and prioritized.

The software runs on standard PCs under the operating systems WindowsXP and WindowsNT. It is object-oriented (C++) and consists of a system core and several tools (plug-ins) which are linked dynamically. Within the core module the GUI is implemented using the class library QT (Trolltech).

3 Road and context model

Road extraction in land consolidation areas is in particular motivated by the high demand for accurate, detailed, and up-to-date information for project monitoring [16]. Therefore, besides using a sophisticated extraction strategy, detailed object and context modeling plays a key role for road extraction in these areas.

3.1 Road model

The road model illustrated in Fig. 2 compiles knowledge about radiometric, geometric, and topological characteristics of roads in form of a hierarchical semantic network. The model represents the standard case, i.e., the appearance of roads is not affected by relations to other objects. It describes objects by means of concepts, and is divided into three levels defining different points of view.

The *real world* level comprises the objects to be extracted. On this level the road network consists of junctions and road links connecting junctions. Road links are constructed from road segments. Road segments and complex junctions are aggregatings of lanes, which in turn consist of pavement and markings.

The *geometry and material* level has a close relation with the concepts of the real world, which connects concepts representing the same object on different levels. This level is an intermediate level which represents the 3D-shape of an object as well as its material [17].

The *image* level describes objects independently of sensor characteristics and viewpoint. Road segments are linked to the bright homogeneous ribbons of the image level in coarse scale. In contrast to this, the pavement as a part of a lane segment in fine scale is linked to the elongated bright region of the image level via the elongated, flat concrete or asphalt region.

3.2 Context model

The road model illustrated above is extended by knowledge about context, which is called context objects. Context is restricted to knowledge about relations of the object of interest to other objects. Background objects such as buildings, trees, vehicles and external GIS data can also be regarded as context objects. Modeling this interaction between road objects and context objects on a local as well as on a global level is a strong aid for guiding the extraction. The context model is divided into two levels [18].

Global context is used to emphasize characteristic parts of road model and to focus on special attributes and aspects of roads which depend on the presence of other objects in large regions. It is used to find areas where the road network can easily be extracted.

Local context describes knowledge about spatially restricted relations between roads and other objects, e.g., buildings and trees. This knowledge supports completion of the road network under unfavorable circumstances, like shadows or occlusions, based on contextual reasoning, i.e., already available information about objects or object parts is used to guide further extraction.

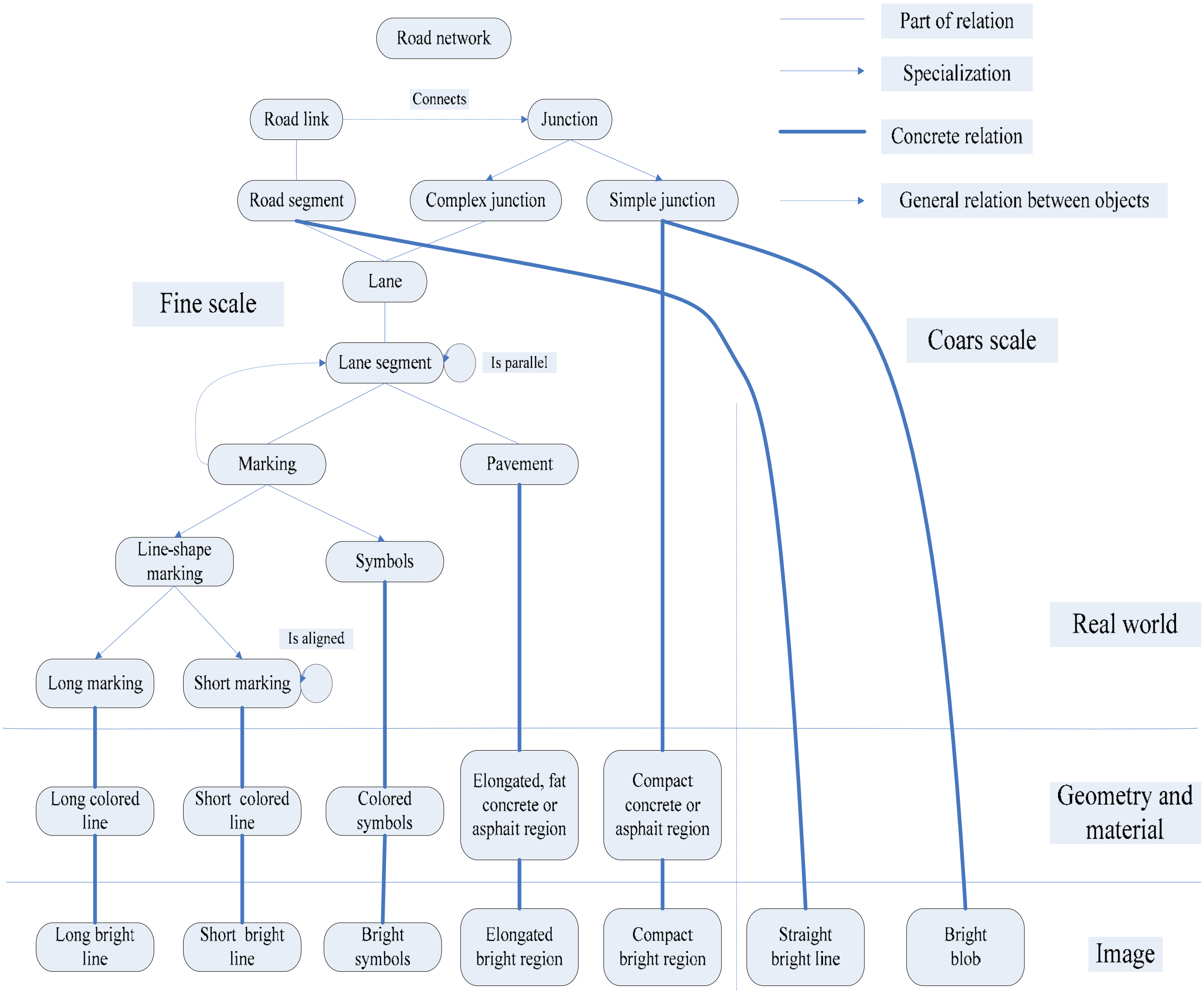


Fig.2 Model for road extraction

4 Data preprocessing and methodology

At the original level of resolution of the road is essentially modeled as bright linear objects with parallel boundaries (geometric model) and a homogeneous area in between (radiometric model). A road may extend from an area with parallel boundaries into an adjacent area. In the first step, the curvilinear structures were detected cursorily. Then the road parallels were detected to build the road segments. At last, the improved Snakes are introduced to connect the road segments to the whole road network.

We need to filter the image and then extract the road network [19]. The diagram in Fig. 2 shows the main process of the extraction.

4.1 Data preprocessing

Tomasi and Manduchi [20] presented a non-iterative scheme for edge preserving smoothing that is non-iterative and simple, which is called domain filtering. If the input image is *I(x, y)*, the output image can be calculated as the flowing Equ.1:

$$\hat{I}(x,y)=\frac{\sum_{i=-s}^{s}\sum_{j=-s}^{s} I(x+i,y+i)w(i,j,x,y)}{\sum_{i=-s}^{s}\sum_{j=-s}^{s} w(i,j,x,y)} \quad (1)$$

In Equ.1 1, *w (i, j, x, y)* is the weight coefficient which is defined by the following Equ.2 and *s* represents the size of the filter window.

$$w(i,j,x,y)=\exp(-\frac{i^2+j^2}{2\sigma_D^2})\exp(-\frac{(I(x+i,y+j)-I(x,y))^2}{2\sigma_R^2}) \quad (2)$$

The expression of weight coefficient (Equ.2) contains two parts. The first part which is related to spatial domain of the image is measured by the Euclidean distance between the central pixel and its neighbors. The more a pixel is near the central pixel, the more its influence is huge. The second part is a similarity function which is measured by the gray difference between the central pixel and its neighbors. The more the difference of neighbor pixels is little, the more its influence is huge.

The filter above mainly includes three parameters: *s*, σ_R and σ_D. These three parameters' relationship is given as the flowing Equ. 3:

$$s = 2*\sigma_D + 1 \qquad (3)$$

According to the test results, when σ_D is for 1 and σ_R is for 20, the digital filtering effect is the best, which can guarantee the effect of smoothing and edge detection and the implementation speed.

4.2 Methodology

The method of road network extraction mainly contains three parts: extracting the curvilinear structures, detecting the road segments and then linking the segments to road network. The followed Fig. 3 describes the road extraction scheme.

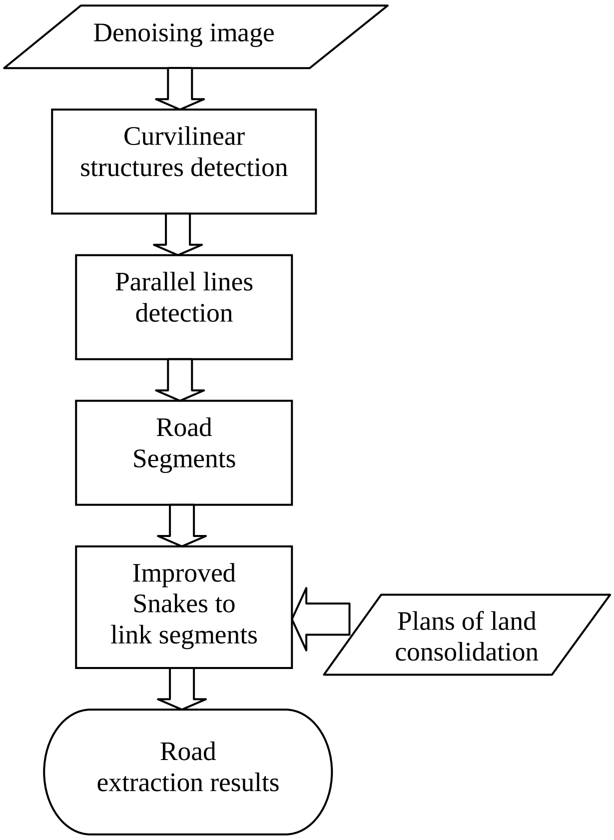


Fig.3 Road extraction scheme

4.2.1 Unbiased curvilinear structures extraction

Steger et al. [21] developed a scheme to extracting curvilinear structures, in which the ridges and ravines are detected by locally approximating the image function by its second or third order Taylor polynomial. Firstly the curvilinear structures of 1D image were detected for example, and then the method was enhanced in 2D image.

The ideal line of width 2*w* and height *h* in 1D is given by:

$$f_p(x) = \begin{cases} h(1-(x/w)^2), & |x| \le w \\ 0, & |x| > w \end{cases} \qquad (4)$$

In order to detect lines with a profile given by Equ.4 in an image *z(x)*, it is sufficient to determine the points where *z'(x)* vanishes. And the magnitude of the second derivative *z''(x)* in the point where *z'(x) =0*

Due to a significant noise of the image, the first and the second derivatives of the z(x) should be estimated by convolving image with the derivatives of the Gaussian smoothing kernel:

$$g_\sigma(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}} \qquad (5)$$

The response, i.e., the estimated derivatives, will be:

$$\begin{aligned} r_p(x,\sigma,w,h) &= g_\sigma(x) * f_p(x) \\ r'_p(x,\sigma,w,h) &= g'_\sigma(x) * f_p(x) \qquad (6) \\ r''_p(x,\sigma,w,h) &= g''_\sigma(x) * f_p(x) \end{aligned}$$

According to Equ.*6*, $x = 0 \Leftrightarrow r'_p = 0$ for all σ, and r''_p takes on its maximum negative value at *x=0* for all σ. Ideal line will be flattened out as σ increases as a result of smoothing.

Curvilinear structures in 2D image of the land consolidation area can be modeled as curves *s(t)*, that exhibit characteristic 1D line profile in the direction perpendicular to the line, i.e., perpendicular to *s'(t)*, which means that the first directional derivative in the direction should vanish and the second directional derivative should be a large absolute value.

According to the analysis above, the main work is to compute the direction of the line locally for each image point. The partial derivatives r_x, r_y, r_{xx}, r_{xy}, and r_{yy} of the image will have to be estimated, and this can be done by the following kernels

$$\begin{aligned} g_{x,\sigma}(x,y) &= g_\sigma(y) g'_\sigma(x) \\ g_{y,\sigma}(x,y) &= g'_\sigma(y) g_\sigma(x) \\ g_{xx,\sigma}(x,y) &= g_\sigma(y) g''_\sigma(x) \qquad (7) \\ g_{xy,\sigma}(x,y) &= g'_\sigma(y) g'_\sigma(x) \\ g_{yy,\sigma}(x,y) &= g''_\sigma(y) g_\sigma(x) \end{aligned}$$

The direction in which the second directional derivative of *z(x,y)* takes on its maximum absolute value can be determined by calculating the eigenvalues and eigenvectors of the Hessian matrix

$$H(x,y) = \begin{pmatrix} r_{xx} & r_{xy} \\ r_{xy} & r_{yy} \end{pmatrix} \qquad (8)$$

The calculation can be done in a numerically stable and efficient way by using one Jacobi

When the image is convolved with the derivatives of a Gaussian kernel, the second directional derivative perpendicular rotation to annihilate the r_{xy} term. As in the 1D case, a quadratic polynomial will be used to determine whether the first directional derivative along (n_x, n_y) vanishes within the current pixel. This point will be given by

$$(p_x, p_y) = (tn_x, tn_y) \qquad (9)$$

where

$$t = -\frac{r_x n_x + r_y n_y}{r_{xx} n_x^2 + r_{xy} n_x n_y + r_{yy} n_y^2} \qquad (10)$$

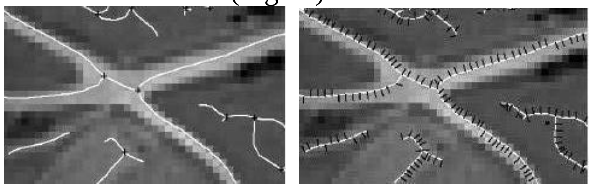
Again, $(p_x, p_y) \in [-0.5, 0.5] \times [-0.5, 0.5]$ is required in order for a point to be declared a line point. As in the 1D case, the second directional derivative along (n_x, n_y), i.e., the maximum eigenvalue, can be used to select salient lines.

The next step is to link the line points detected above into lines.

Starting from the pixel with maximum second derivative, lines will be constructed by adding the appropriate neighbor to the current line. Since it can be assumed that the line point detection algorithm will bring a fairly accurate estimate for the local direction of the line, only three neighboring points that are compatible with this direction are examined. For example, if the current point is (c_x, c_y) and the current orientation of the line is in the interval [22.5°, 67.5°], only the points (c_{x+1}, c_y), (c_{x+1}, c_{y+1}) and (c_x, c_{y+1}). The choice regarding the appropriate neighbor to add to the line is based on the distance between the respective sub-pixel line locations and the angle difference of the two points. Let $d = \|p_2 - p_1\|_2$ be the distance between the two points and $\beta = |\alpha_2 - \alpha_1|$ such that $\beta \in [0, \pi/2]$ be the angle difference between those points. The neighbor that is added to the line is the one that minimizes $d + c\beta$. In the current implementation, $c = 1$ is used.

This algorithm will select each line point in the correct order. At junction points, it will select one branch to follow without detecting the junction, which will be detected later on. The algorithm continues to add line points until no more line points are found in the current neighborhood or until the best matching candidate is a point that has already been added to another line. If this happens, the point is marked as a junction, and the line that contains the point is split into two lines at the junction point.

The following figures show that the linked line points (Fig. 4) and the results of curvilinear structures extraction (Fig. 5).



a b

Fig.4 Line points

a b

Fig.5 Curvilinear structures

4.2.2 Road segment detection

In the high resolution image, the roads perform as ribbon features. So it is an important characteristic of road in high resolution image that the side line is parallel.

In this section parallel lines in the image were detected. In order to be classified as parallel, two segments have to fulfill the following conditions which can help us to detect the parallel in a part of the image [22]:

1) The difference of the two directions must be below a threshold. This threshold depends on the lengths of the segments, since the direction of longer lines is computed more accurately.

$$\alpha \le \tau + \frac{\omega\tau}{\max(l_1, l_2)} \qquad (11)$$

l_1 and l_2 in the Equ.11 represent the length of the roads, τ represents the threshold that has been set, and ω is for 1.

2) The two segments must overlap. To determine overlap a line in the direction of the bisection of the angle formed by the two segments is computed, and the end points of both segments are projected onto the line. The segments are said to overlap, if and only if the projected lines overlap.

3) The distance of the two segments must not exceed extracted polygons a certain threshold corresponding to the maximum width of the roads.

As part of the radiometric road model, the area between two parallel polygon segments is investigated next. According to the model this area should be bright and homogeneous. In an attempt to include road markings into the model, we break up the area under consideration into slices parallel to the direction of the bisection of the two segments (see Fig. 6). Mean and variance of the resampled grey values within each slice are computed.

A pair of parallel segments is only accepted, if the mean falls into a predefined range and the variance is smaller than a given threshold. The results of this step are called *modified parallels*.

Obviously, parts of the road where no parallel segments exist. In order to overcome this deficiency, segments next to accepted road segments are recursively investigated for homogeneity of the adjacent area (see Fig. 7). They are accepted if the same homogeneity criteria as above are fulfilled. The results of this step are called *extended parallels*.

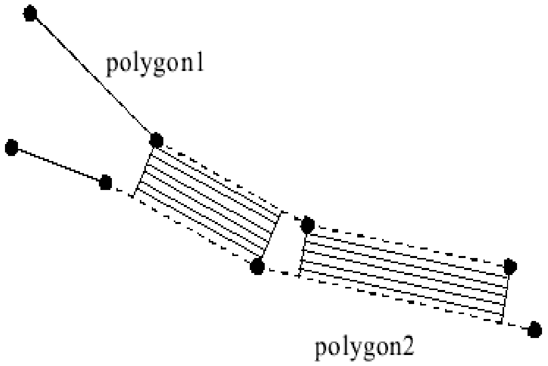


Fig.6 Statistical detection areas

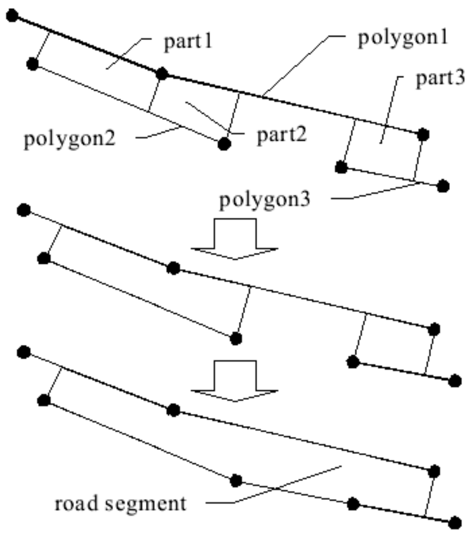


Fig.7 Extended parallels

The result of the detected road segments is shown in Fig. 8. Then we integrate the extracted curvilinear structures and the road segments to get the right road segments.

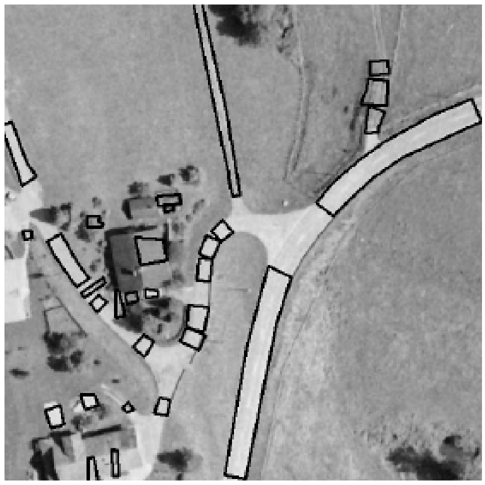


Fig.8 Combination results

4.2.3 Link segments

In the third step, the road segments have already been extracted, but the segments are disconnected because other objects such as trees shadow the roads on the intersections. So we need to connect the segments to construct the whole networks using an improved Snakes model.

Snakes, which is also called Active Contour Models, was firstly presented by Kass *et al.* [23] to extract the contour of object in the image. The original Snakes are modeled as time-dependent curves defined parametrically as

$$\vec{v}(s,t) = (x(s,t), y(s,t))|_{0 \le s \le 1} \quad (12)$$

Where s is proportional to the arc length, t the current time, and x and y the curve's image coordinates.

According to the model describe above, we can write its energy functional as

$$E^*_{snake} = E_{\text{int}}(\mathbf{v}) + E_{image}(\mathbf{v}) + E_{con}(\mathbf{v}) \quad (13)$$

where E_{int} represent the internal energy of the spline due to bending, E_{image} gives rise to the image forces, and E_{con} gives rise to the external constraint forces.

The internal spline energy can be written

$$E_{\text{int}}(\mathbf{v}) = \frac{1}{2}\int_0^1 \alpha(s)\left|\frac{\partial \mathbf{v}(s,t)}{\partial s}\right| + \beta(s)\left|\frac{\partial^2 \mathbf{v}(s,t)}{\partial s^2}\right| ds \quad (14)$$

The spline energy is composed of a first-order term controlled by $\alpha(s)$ and a second-order term controlled by $\beta(s)$. The first-order term snakes the snake act like a membrane and the second-order makes it act like a thin plate. Adjusting the weights $\alpha(s)$ and $\beta(s)$ controls the relative importance of the membrane and thin-plate terms.

The image energy can be written

$$E_{image}(\mathbf{v}) = -\int_0^1 P(\mathbf{v}(s,t))ds \qquad (15)$$

where $P(\mathbf{v}(s,t)$ is a function of the image. One typical choice is to take $P(\mathbf{v}(s,t)$ to be equal to the magnitude of the image gradient, that is

$$P(\mathbf{v}(s,t) = |\nabla I(\mathbf{v}(s,t)| \qquad (16)$$

where I is either the image itself or the image convolved by a Gaussian kernel.

The snakes can detect the contour well, but are only effective when the initial position is close to the desired solution. However, they are very sensitive to initial conditions. They can easily get caught in local minima when the desired outline presents large concavities the force the snake to extend itself.

To improve traditional snakes' convergence properties, Neuenschwander *et al*. [24] developed a boundary-value method with acts like *ziplock* plastic bags. The user specifies end points in the vicinity of a clearly visible edge segment. The algorithm first optimizes the location of the user-supplied points on the gradient image, and then calculates the edge directions at these points using both the initial image and its gradient.

As illustrated by Fig. 9, the ziplock snakes are divided into three parts by force boundary points and vertex points. The points between vertex points and boundary points are called active points. Other points are called passive points.

The ziplock snakes are initialized by Bezier-curves, which can be generated by the two vertex points. During the next ongoing iterative optimization process the process the image potential P is turned on progressively for all snake vertex points, starting from extremities. The iteration continues until the curves converge minimum energy.

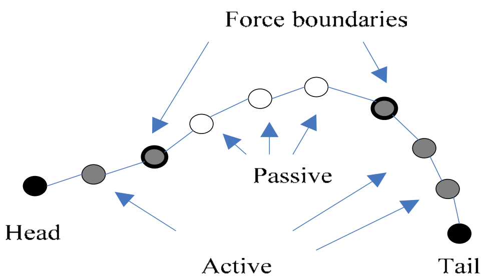


Fig.9 Schematic Ziplock Snake

In the high resolution image, the roads perform as ribbon features but line features. Fua and Leclerc[25] improved the snakes into ribbon snakes(Fig. 10) and modeled roads as ribbons whose smoothly curved edges are approximately parallel. A ribbon is implemented as a polygonal curve forming the center of the road. They added a third vector to the traditional snakes as the following Equ. 17:

$$\vec{v}(s,t) = (x(s,t), y(s,t)), w(s,t)|_{0\le s\le 1} \qquad (17)$$

w(s, t) represents the width of road.

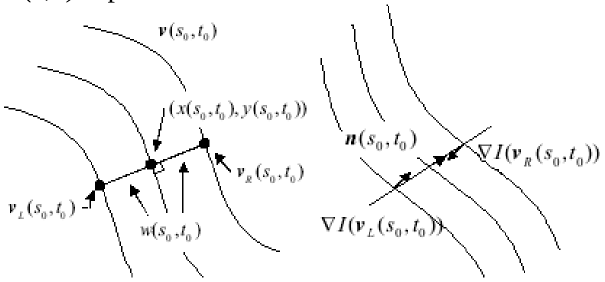


Fig.10 Ribbon snakes

Thus, the *ziplock snakes* are used to extract the edge of road efficiently and the ribbon snakes extract the ribbon feature well, so we integrate the two models and the already extracted road segments above to extract the whole road network.

5 Application

In order to demonstrate the functionality of the system developed in this study, the images, plans of land consolidation, and maps of situation of land utilization were imported to the database, which was to ensure the system would work correctly before it was distributed to users.

The study area is Changgou town which located in south-west of Fangshan district, at the confluence of the Juma River, covering approximately 25km2. The geographic coordinates (latitude/longitude) approximately range from 115°45' 46'' E, 03°08'00''N to 115°46'25''E, 03°10'39''N.This area is characterized by rolling topography and flourishing vegetation.

Three SPOT5 images, acquired on 12 October 2002, 6 June 2004 and 29 September 2006, without any clouds/hazes, are used in this study. A SPOT 5 image has four multi-spectral bands (i.e. near-infrared (NIR), red, green, and Short Waved-length Infrared) with t10-metre spatial resolution and one panchromatic band with 2.5-metre spatial resolution. Both dates of imagery were geo-referenced to a Transverse Mercator projection and Krasovsky spheroid with an RMSE of 1 pixel. It was necessary to radiometrically normalize the multiple dates of remote sensor data even though they were obtained on near anniversary dates.

The diagrams in Fig. 11-12 present an example to extract the road network in the study area by using the system. It shows the high resolution image and plans of land consolidation, and gets the changes of roads after the project.

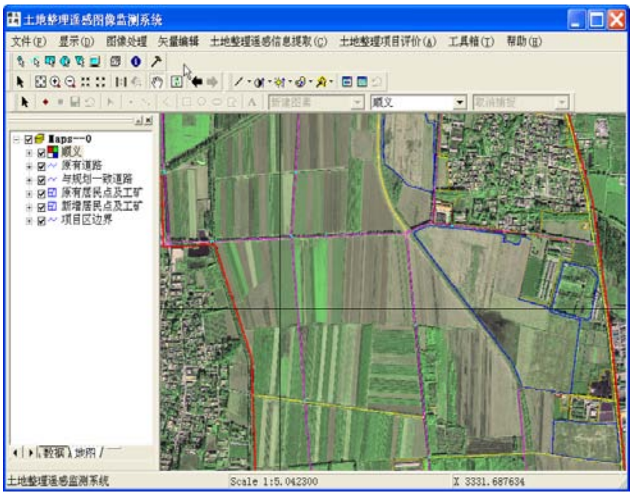


Fig.11 The system interface

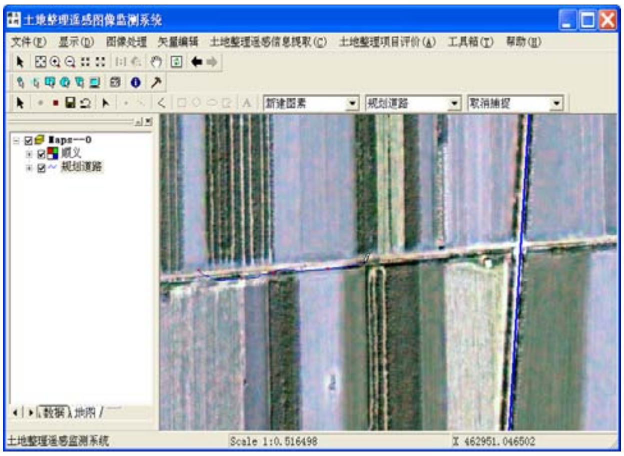


Fig.12 The system interface

In more detail, an analysis of system implementation results shows that: the system is practical and useful, and regarded as a useful tool. The system presented in this paper is preliminary outcomes of ongoing studies. The system will be further developed, e.g. developing more effective method of automatic feature extraction.

6 Conclusions and future works

An integrated road network extraction system has been briefly described. This system is intended to be an example for other land consolidation area. Interface, modules and database are carried out as the components of this system, in which road network automatic extraction model is the most important component of the system. The system in this study provides easy access for extracting roads network in the study area, and a result for land management department of the nation.

By incorporating multiple knowledge, the road and context model has been established the problematic areas caused by shadows, occlusions etc. can be often handled. Based on the extracted roads, the road junctions are generated and modeled, thus the system provides an up-to-date and complete road network for practical uses. According to the above algorithm, other linear features such as drains and pipelines could also be extracted in this system. However, our system is mostly intended for rural areas. The algorithm should be improved to be suitable for urban areas.

The high-resolution images are preferable due to use of width and variance information for road net work extraction. On the other hand, the multispectral information should also be fully used. The concept of automation has shown to be excellent for practical applications, as there is always an editing option, if some automation fails due to low image quality, disturbances or other effects. And the automatic method should be deeply studied and widely used in the future.

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