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Road Network Extraction Based on Self-organizing Map from IKONOS Imagery

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Abstract. Automated road information extraction in transportation provides the means for creating, maintaining, and updating in the aspect of transportation network databases concerning traffic management, automated vehicle navigation, and guidance. It is given a strong motivation for research on automatic interpretation of satellite imagery. This paper presents an automatic method for extraction of road seeds from high-resolution satellite imagery. Firstly, we focus on finding the seed points in road segments using methods of the self-organizing map (SOM). Then an approach of road tracked is presented, which searches for connected points in the direction and the candidate domain of road. The study on the geographical information system (GIS) with high-resolution satellite imagery is given in this paper.

Keywords: Road networks extraction, Self-organizing map, Road Tracking, High resolution satellite imagery

自己組織化マップに基づくIKONOS画像から道路ネットワーク抽出

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あらまし. 衛星画像からの自動的な道路情報抽出は，交通管理，自動車自動操縦およびガイダンス用の道路ネットワーク・データ・ベースを構築・維持・更新するための手段を提供する．それは、衛星画像による自動的な構造解析の研究に対して，強い動機づけを与えている．本論文は、高解像度衛星画像から道路シード抽出ための一つの方法を示す．まず，自己組織化マップ（SOM）の方法を用いて，道路セグメントでシード点を見つける．それから，道路方向や道路候補領域に関係のある点を捜し，道路追跡を行う．これらの手法が有効であることを高解像度衛星画像に適用することで示す．

キーワード： 道路ネットワーク抽出，自己組織化マップ，道路追跡，高解像度衛星画像

1 Introduction

The high-resolution IKONOS satellite imagery has provided the world with the first source of commercially available, marked the beginning of a new era in earth observation. It can provide accurate and up-to-data information for extraction and maintenance of road databases, and so on. Automated road information extraction in transportation provides the means for creating, maintaining, and updating transportation network databases for traffic management, automated vehicle navigation, and guidance. These data are frequently used in making critical decisions, such as emergency response, evacuation, or incident management. Updating road map is a time-consuming operation when performed manually. Due to the need for efficient acquisition and update of data for Geographic Information Systems (GIS), the automatic road extraction from high-resolution satellite and aerial imagery have become a hot issue for more than twenty years. The automatic extraction methods hold potential for reducing database development cost and turnaround time. When the factors such as image resolution, degradation of image quality, obstructions, and presence of linear but non-road features are taken into consideration, the task of road identification becomes overwhelmingly complex.

Until now a large number of approaches for road extraction have been proposed and published. The road extraction processes have many different forms according to the imagery's spatial resolution. In low-resolution imagery (i.e., ground resolution more than 2m per pixel), roads correspond to lines whereas in a resolution of 0.2m-0.5m they can be described as elongated homogeneous areas [2]. The global network structure of the road can be seen clearly and small disturbances like shadows and cars can be easily avoided in low-resolution imagery. In high-resolution imagery, the accuracy of geometrical properties like width and curvature is much better. A multi-resolution approach for automatic extraction of roads from digital aerial imagery is presented [3], [9].

Besides a classification of road extraction schemes in low- and high-resolution imagery, the strategies of road extraction fall into two broad categories: semi- and fully-automatic. A semi-automatic information-theoretic active approach to fast tracking in satellite images of low-curvatures low-resolution roads is presented [5]. A semi-automated approach of elongated region based on analysis for 2D road extraction from high-resolution imagery is presented [4]. In fully automatic schemes, knowledge sources such as GIS or geographical database [6], [11], heuristics [8], [9], [10] and stochastic methods [1] are used to initialize the road tracking.

The extraction of road networks from aerial and satellite imagery is a fundamental image analysis operation. In Doucette et al., they presented a self-organizing road map (SORM) algorithm, which combines straight K-medians spatial clustering approach with a post-convergence node linking MST (minimum spanning tree) algorithm. The limitation of node linking was applied in the opened loop candidate domain. Our work focus on road network extracting based on neural networks, and can overcome the above limitation. Firstly, we propose in this paper to use method of self-organizing map, which is inspired from a specialized variation of Kohonen's self-organizing map (SOM) neural network algorithm, in order to find the seeds of road networks. Next, an approach of road tracked is presented, which searches for connected points in the direction and the candidate domain of road. Then, results of simulations are shown for road networks extraction with this method. The study on the geographical information system (GIS) with high-resolution satellite imagery is given in this paper.

2 Algorithm

2.1 Self-Organizing Maps

Kohonen's Self-Organizing Map (SOM) is one of the most popular artificial neural network algorithms. The basic Self-Organizing Map (SOM) can be visualized as a sheet-like neural-network array, the cells (or nodes) of which become specifically tuned to various input signal patterns or classes of patterns in an orderly fashion. The learning process is competitive and unsupervised, meaning that no teacher is needed to define the correct output (or actually the cell into which the input is mapped) for an input. In the basic version, only one map node (winner) at a time is activated corresponding to each input. The locations of the responses in the array tend to become ordered in the learning process as if some meaningful nonlinear coordinate system for the different input features were being created over the network.

Here, we proceed with a brief description of its function. Assume that some sample data sets have to be mapped onto the array depicted, the set of input samples is described by a real vector $x(t) \in R^n$ where t is the index of the sample, or the discrete-time coordinate. Each node i in the map contains a model vector $m_i(t) \in R^n$, which has the same number of elements as the input vector $x(t)$.

The stochastic SOM algorithm performs a regression process. Thereby, the initial values of the components of the model vector, $m_i(t)$, may even be selected at random. In practical applications, however, the model vectors are more profitably initialized in some orderly fashion, e.g., along a two-dimensional subspace spanned by the two principal eigenvectors of the input data vectors.

Any input item is thought to be mapped into the location, the $m_i(t)$ of which matches best with $x(t)$ in some metric. The self-organizing algorithm creates the ordered mapping as a repetition of the following basic tasks:

1. An input vector $x(t)$ is compared with all the model vectors $m_i(t)$. The best-matching unit (node) on the map, i.e., the node where the model vector is most similar to the input vector in some metric (e.g. Euclidean) is identified. This best matching unit is often called the winner.
2. The model vectors of the winner and a number of its neighboring nodes in the array are changed towards the input vector according to the learning principle specified below.

The basic idea in the SOM learning process is that, for each sample input vector $x(t)$, the winner and the nodes in its neighborhood are changed closer to $x(t)$ in the input data space. During the learning process, individual changes may be contradictory, but the net outcome in the process is that ordered values for the $m_i(t)$

emerge over the array. If the number of available input samples is restricted, the samples must be presented reiteratively to the SOM algorithm.

Adaptation of the model vectors in the learning process may take place according to the following equations:

$$\begin{cases} m_i(t+1) = m_i(t) + \alpha(t)[x(t) - m_i(t)] \\ \qquad\qquad\qquad\qquad \text{for each } \; i \in N_c(t) \qquad (1) \\ m_i(t+1) = m_i(t) \qquad\qquad \text{otherwise,} \end{cases}$$

where t is the discrete-time index of the variables, the factor $\alpha(t) \in [0,1]$ is a scalar that defines the relative size of the learning step, and $N_c(t)$ specifies the *neighborhood* around the winner in the map array.

At the beginning of the learning process the radius of the neighborhood is fairly large, but it is made to shrink during learning. This ensures that the global order is obtained already at the beginning, whereas towards the end, as the radius gets smaller, the local corrections of the model vectors in the map will be more specific. The factor $\alpha(t)$ also decreases during learning.

One method of evaluating the quality of the resulting map is to calculate the average quantization error over the input samples, defined as

$$node \quad c = \arg\min_i \|x - m_i(x)\| \qquad (2)$$

where c indicates the best-matching unit for x. After training, for each input sample vector the best-matching unit in the map is searched for, and the average of the respective quantization errors is returned.

2.2 Approach of Road Tracked

An approach of road tracked is used in linking corresponding two seed points of the road network analysis. It assumes that the road direction changes are likely to be slow and roads are unlikely to be short. Giving a road seed start point from the edge of processed image. Searching for connected two closest seed points in the direction of the road according to white candidate domain. Then linking corresponding two seed points.

Supposes the initial seed points are near by the side of image. The order is from left to right, and from top to bottom. The rules of road tracked are built, which are stated as following:

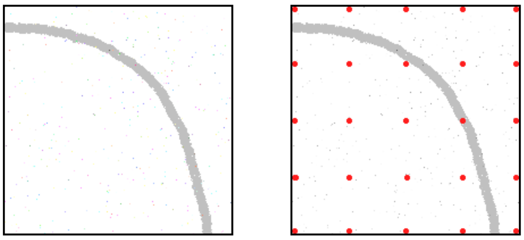
1. The path vector direction is priority. Namely, the deflection angle θ of linked line between relational seeds on the candidate domain is considered smallest.

$$\min\theta = \min \;\; arccos\left(\frac{\vec{A}\bullet\vec{B}}{|A||B|}\right) \qquad (3)$$

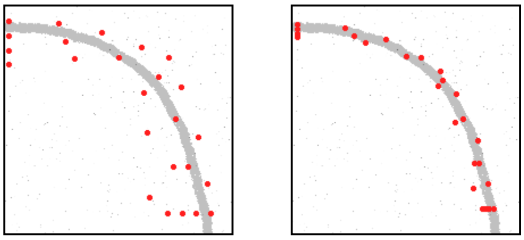
2. The linked line should be fallen in the candidate domain of road.
3. Roads are unlikely to be short, moreover are continual.

2.3 Simulation of Sample Image

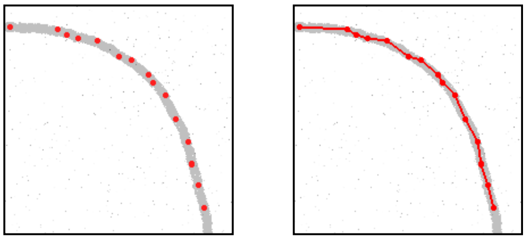
Fig.1 demonstrates the simulation process of a sample image with 1% random noise. The input is the (x, y) coordinates for each sample. The initially defined chain keeps its structure as it moves to attach itself to the grey pixels. Fig.2 (c)-(e) demonstrate neuron ordering. The size of the neighbourhood kernel is typically setup to be a function of time (epoch). Initially it is large, and a single neuron carries along with it many neurons (ordering stage of the SOM), but it progressively shrinks until only the winning node is updated in the last iterations. Similarly, the learning rate factor approaches 0 as the number of epochs increases, to facilitate the stabilization of the solution.



(a) Sample Image (Add 1% Random Noise) (b) 50 Pixels Initialization Grid



(c) after twice iterations (d) after 4 time iterations



(e) after10 time iterations (f) Points Linked

Fig. 1 Simulation Process of a Sample Image with 1% Random Noise

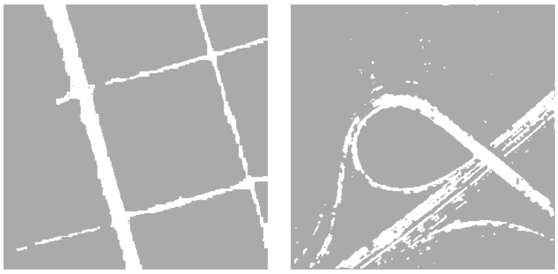
3 Simulations of Applied in Road Network Extraction

3.1 Outline of Approach

First of all, preprocess for original satellite imagery are carried out by fuzzy reasoning approaches, in order to find the candidate domain of road. Road category maps are SOM that have been organized according to road similarities, measured by the similarity of the short contexts of the road segments. Conceptually interrelated road segments tend to fall into the same or neighboring map nodes. Nodes may thus be viewed as road categories. Although no a priori information about classes is given, during the self-organizing process a model of the road classes emerges. As mentioned in the above introduction, the road seeds are firstly found based on self-organizing map from the image with the candidate domain of road. Then the connected points in the direction and the candidate domain of road are linked according to the rule of road tracked.

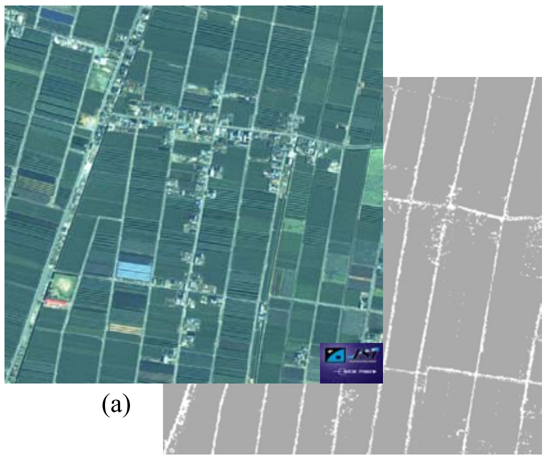
(a) Image of Field Road (b) Image of Overpass Road

Fig. 2 Original Satellite Imagery (300×300 pixels)



(a) Field Road (b) Overpass Road

Fig. 3 Preprocess Results for Original Satellite Imagery (300×300 pixels)



(a)

(b)

Fig. 4 Large Original Satellite Imagery (1000×1000 pixels) (a) The Large Image with Field Road (b) Preprocess Result for Large Image

3.2 Small Image (300×300 pixels)

Firstly, we give initialization grid spacing with 30 pixels for the small image (300×300 pixels, shown in Fig. 2 (a), (b)). The results of SOM and road tracked process for field road image and overpass road image are shown in Fig. 5 and Fig. 6 respectively. Next, in order to reduce computational quantity and to raise computing speed (See Fig. 11), the simulations with 50 pixels initialization grid spacing are carried out in the same small image. The processing results are shown in Fig. 7 and Fig. 8 respectively.

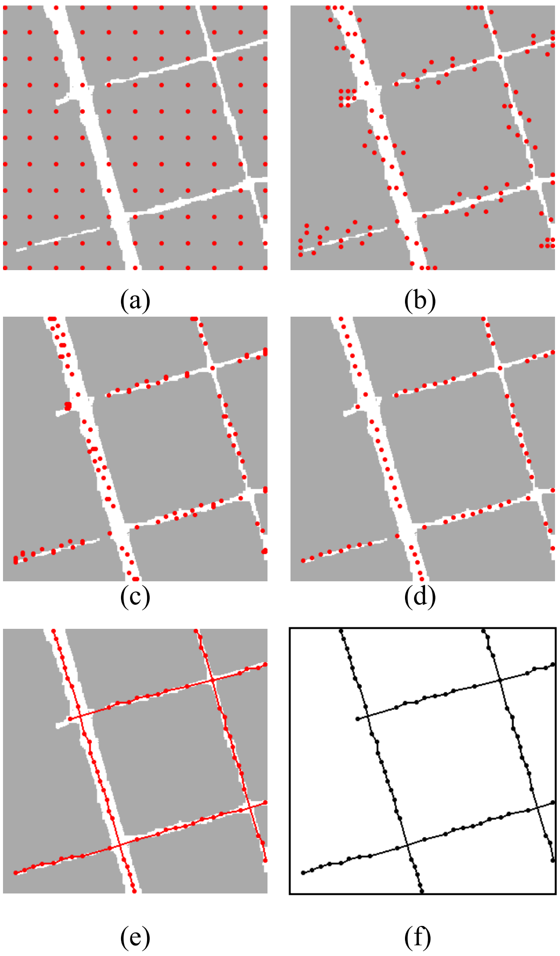


Fig. 5 The Process Results for the Small Field Road Image (30 Pixels Initialization Grid) (a) 30 Pixels Initialization Grid (b) After twice iterations (c) After 4 time iterations (d) After10 time iterations (e) Road Tracked Linking (f) Road Network Extraction

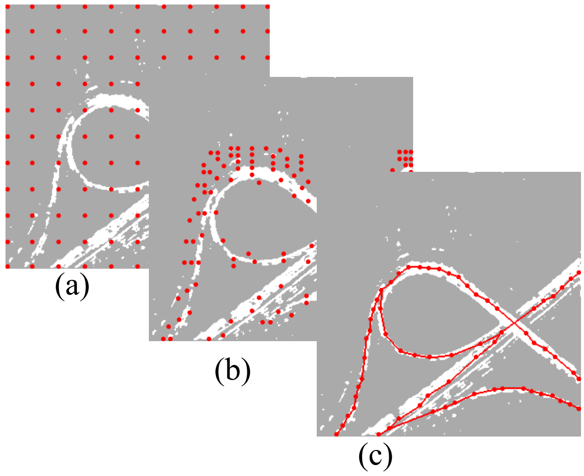


Fig. 6 The Process Results for the Small Overpass Road Image (30 Pixels Initialization Grid) (a) 30 Pixels Initialization Grid (b) After twice iterations (c) Road Network Extraction

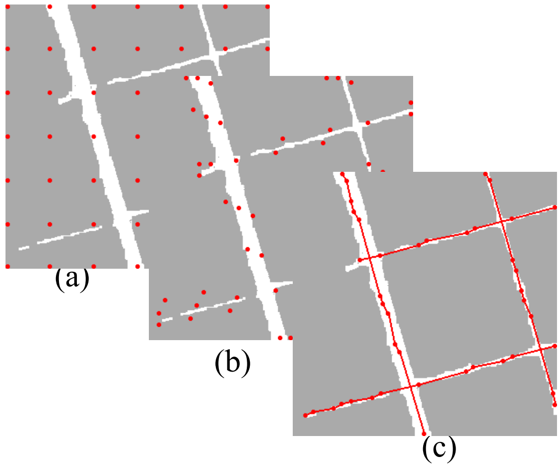


Fig. 7 The Process Results for the Small Field Road Image (50 Pixels Initialization Grid) (a) 50 Pixels Initialization Grid (b) After twice iterations (c) Road Network Extraction

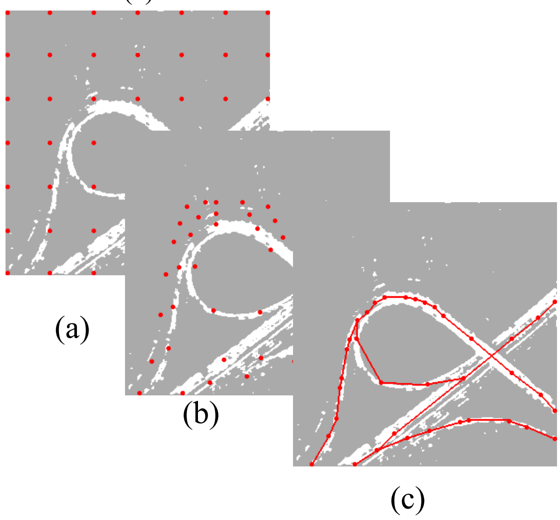


Fig. 8 The Process Results for the Small Overpass Road Image (50 Pixels Initialization

Grid) (a) 50 Pixels Initialization Grid (b) After twice iterations (c) Road Network Extraction

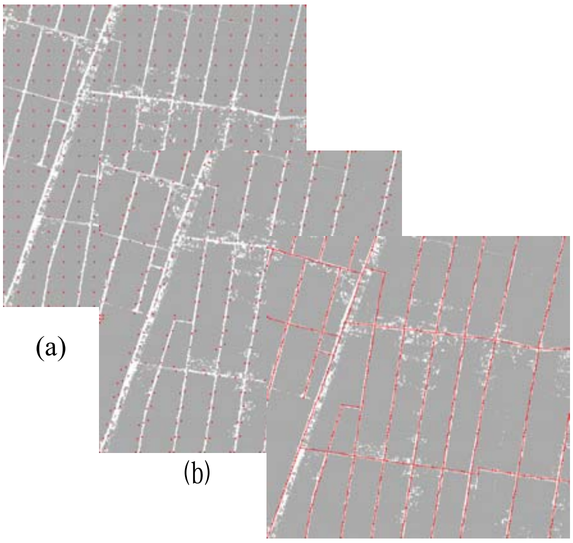


Fig. 9 The Results of SOM and Road Tracked Process for the Large Field Road Image (a) 50 Pixels Initialization Grid (b) After twice iterations (c) Road Network Extraction

3.3 Large Image (1000×1000 pixels)

From the above results shown in Fig. 7 and Fig. 8, we can find that when the initialization grid spacing are increased, there are not any influence in the processing image included straight line roads. To the contrary, there are some influences in the processing image included curve roads. Therefore, we can profit from the above processing results, the initialization grid spacing with 50 pixels are given in the processing of large field road image (1000×1000 pixels, shown in Fig. 4 (a)).

3.4 The Rate of Renewal and the Calculation Time

Fig. 10 shows that the rate of renewal is equal to zero approximately after 8 times of study, namely, it means the study process tends to stably.

4 Conclusion and Discussion

Fig. 3 and Fig. 4 (b) are the preprocess results about the candidate domain of road from the original satellite imagery respectively, which are based on fuzzy reasoning approach. The simulations of road network extraction have been carried out on different images (shown in Fig. 2, and Fig. 4 (a)). We can see that the seed points converge on the road candidate domain by the studying process, and then the seed points are linked based on the road tracked.

The central topic of the research in our work is natural road network extraction. A semi-automated approach to 2D road delineation from high-resolution imagery is presented. The goal of the SOM process is to provide an approach to road centerline delineation from high-resolution imagery that is independent of conventional edge definition.

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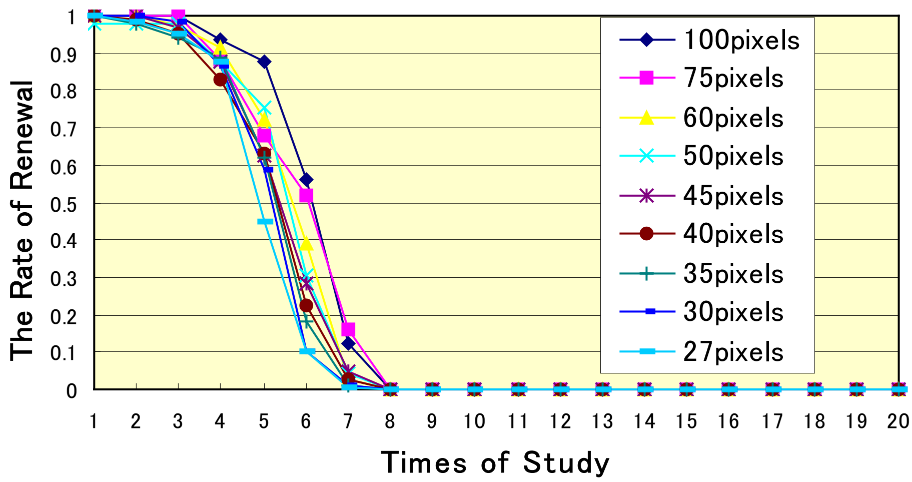

Fig. 10 The Rate of Renewal

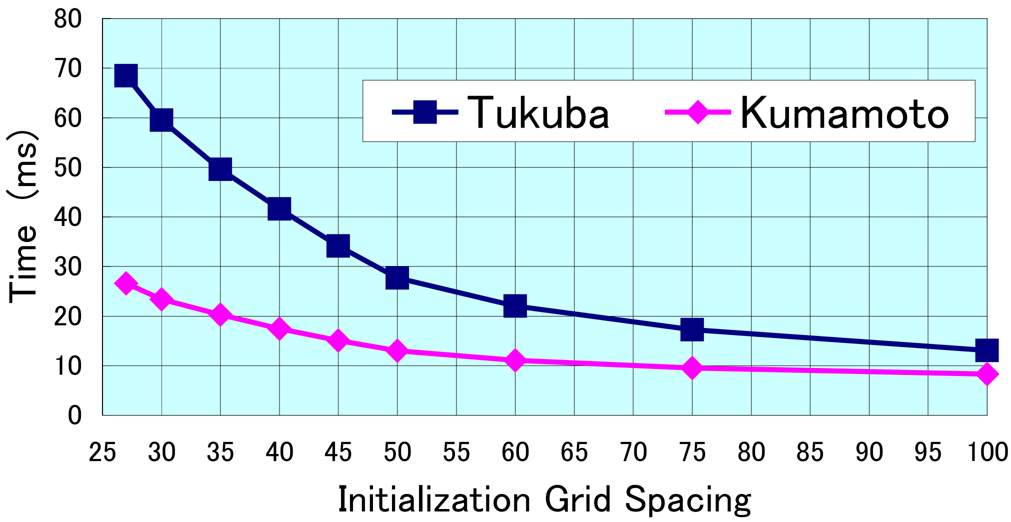

Fig. 11 The Relation of Initialization Grid Spacing and Calculation Time