MARKOV RANDOM FIELD FOR ROAD EXTRACTION APPLICATIONS IN REMOTE SENSING IMAGES

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ABSTRACT:

Bayesian methods coupled with Markovian frameworks has several applications in remote sensing images processing, such as the pixel level applications like filtering, segmentation and classification, and the higher level applications like object recognition and organization etc. This article illustrates the powerfulness of Markovian model at two levels for the road extraction problem in remote sensing images. In order to obtain the final road network, one of the low level applications is using Gaussian Markovian model to segment road target in images and then treat with the original segmentation by the line segment match method and mathematical morphology. For the sake of renewing the complete road network, one of the high level applications detects the basic road sections by homogenous texture and line segment match method, and then organizes the basic road sections in combine with context through adopting Markovian model. Experimental results show that Markovian model has good road segmentation results and high ability to interpret road network.

Ⅰ. INTRODUCTION

With the development of remote sensing technology, more and more remote sensing data are available, thus people can obtain high-resolution images wherever they want. However, the applications of these images are very limited, because of the immature image processing technology, which needs an improvement. How to extract road network automatically from RS images is one of the technical problems puzzling people for a long time, and it has not been well resolved. If we take the traditional way to extract road network manually, it must be a huge waste of time and effort. Therefore, it is urgent to study a fast and effective automatic road extraction method in RS images to accelerate their applications in many areas.

Actually, the fact that how to extract road network from RS images is a problem of target recognition and‘best’decision-making. A well adapted method is bayesian theoretic, which permits us to introduce as much knowledge as possible in decision process and provides the optimal scheme in probability. A powerful tool to introduce prior knowledge is markovian model, as it can be able to describe spatial relationships between the gray-levels or labels of the considering features. Thus, it is possible to find a rational method to deal with this problem through markovian model coupled with bayesian method.

In the following, we illustrate this property and generality of markovian methods according to road extraction problem in two parts. First, an example is given at pixel level, in order to extract road network, we use Gaussian markovian model to segment road target in images and then treat with the original segmentation by the line segment match method and mathematical morphology. In the second part, a higher level application of markovian model is proposed to organize the basic road sections in combine with context and then restore the whole road network.

2. PIXEL-LEVEL ROAD SEGMENTATION

Markov random fields are widely used for low-level applications like filtering, segmentation and classification. Among them, such as segmentation or classification, its aim is to search for a label image. The purpose of road extraction is to label road target as one class and the others as another or even more. The following will describe how to extract road target with markovian model, and knowledge about markov random field theory can refer to paper [1][2][3].

2.1 MAP-MRF framework

Define an image F , size $m \times n$,a set of sites in F is denoted by $S = \{s_1, s_2, \cdots, s_{m*n}\}$,and a realization of F is denoted by $f = \{f_{s_1}, f_{s_2}, \cdots, f_{s_{m*n}}\}$. as image F is classified, every pixel belongs to one class or one label ,and then we can get a label field, denote this field by G ,and a realization of G is denoted by $g = \{g_{s_1}, g_{s_2}, \cdots, g_{s_{m*n}}\}$, $g_s \in \wedge = \{1, 2, \cdots, L-1\}$, L is the number of the class.

Road segmentation problem can be seen as the most probable configuration G according to the observation F , it means that the solution corresponds to the maximum of the conditional probability distribution given the observation F .Using bayes rules:

$$p(G \mid F) = \frac{p(F \mid G)p(G)}{p(F)} \qquad (1)$$

Assume that the label field G is a markov random field, then $F|G$ is also a markov random field and the proof can be seen in[1], with the MRF-Gibbs equivalence

$$p(G|F) \propto p(f|g)p(g) \propto e^{\ln p(f|g)-U(g)} \propto e^{-U(g|f)} \quad (2)$$

Where: $U(g)=\sum_{c\in C} U_c(g)$

Considering the independence between pixels, then:

$$p(f|g)=\prod_s p(f_s|g_s)$$

Further assume that the image was corrupted by Gaussian White Noise with a σ^2 variance, we may writ

$$U(g|f)=\sum_{s\in S} -\ln p(f_s|g_s)+\sum_{c\in C} U_c(g) \quad (3)$$

thus: $$p(f_s|g_s)=\frac{1}{\sqrt{2\pi\sigma}}\exp-\frac{(f_s-g_s)^2}{2\sigma^2} \quad (4)$$

From formula 2, it is obvious to see that the maximum a posteriori probability corresponds to the minimum energy function, as the energy function is nonconvex, it can be solved by means of simulated annealing algorithm.

2.2 Application in road segmentation

In road segmentation application, the most important thing is to identify the parameter values, and it is included both in the conditional probability energy and the prior probability energy, as the following shows:

1） conditional probability energy
2）
Assume that the image can be divided into L classes and corrupted by Gaussian Noise, and then there will be $2*L$ parameters $\{\mu_1,\sigma_1,\mu_2,\sigma_2,\cdots,\mu_L,\sigma_L\}$ in conditional probability energy function, which includes the mean and variance of the whole classes.

3） prior probability energy

Define the prior energy function $U_c(g)$ in using Ising model:

$$U_c(g)=(g_s,g_t)_{(s,t)} \begin{aligned} &=-\beta \quad && g_s=g_t \\ &=+\beta \quad && g_s\neq g_t \end{aligned} \quad (5)$$

Where: β is a coupling parameter controlling the homogeneity of the regions.

Thus, the overall parameters can be denoted by $\{\mu_1,\sigma_1,\mu_2,\sigma_2,\cdots,\mu_L,\sigma_L,\beta\}$.

After learning all the parameter values in energy function, we can get the minimum energy by means of simulated annealing algorithm and obtain the optimal label result. The following is the major processing stepts:

1) Giving the class number L, and then learning $2*L$ parameter values $\{\mu_1,\sigma_1,\mu_2,\sigma_2,\cdots,\mu_L,\sigma_L\}$ through a set of training data.

Parameter β is chosen between 0.5 and 1.

2) Getting the original segmentation result g_0 through Maximum Likelihood probability $p(f|g)$.

3) Relabeling every pixel in the original result g_0 in using Gibbs sampler or Metropolis sampler, if we accept the Gibbs sampler to relabel the pixel, then:

3.A Assume the initial temperature T_0 ,and k is the number of current iterations. For pixel s , we calculate the local conditional probability $p(g_s|V_s)$, and then relabel pixel s with a new value according to its local probability distribution. After traveling the whole pixels in the image, we work out the total energy U_k in the image.

3.B If $\Delta=U_k-U_{k-1}<\delta$, then g_k is the final label result, if not ,turn down the temperature T, and return to step(3)。

In order to have visual effects, we process the RS image (fig.1) of Athens with the proposed markovian segmentation method, and fig.2 shows the result with three different labels, in which one label in black represents road target.

Original extracted road result can be obtained from fig.2 (in black), of course, there are still some non-road pixels, which can be eliminated by line segment match method[5][6]and its improvement[7],fig.3 shows the perfect extracted road result.

Finally, the road central line is obtained from fig.3 in using mathematical morphological methods such as thinning, trimming, and fig.4 shows the final result.

Fig.1 Original image

Fig.2 Segmentation results with MRF model

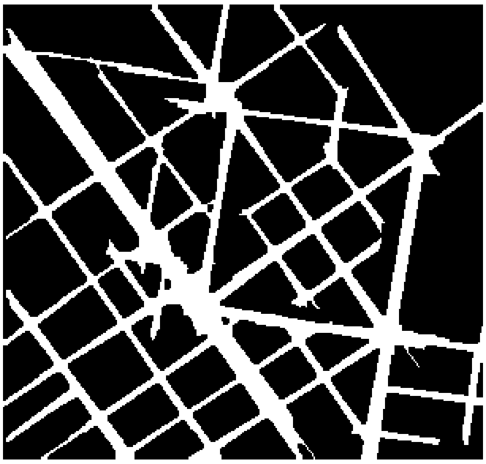

Fig.3 Extracted results with improved line segment match method of fig2.

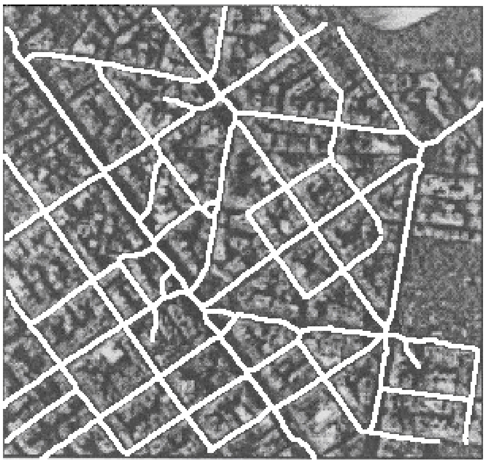

Fig.4 Road extracted results overlapped with original image.

3. HIGN-LEVEL ROAD SEGMENT ORGANIZATION

Due to the complexity of road extraction problem, there are some false road segments or road cracks after the image processed with common road extraction methods. As the fig.5 shows the extracted road from IKONOS image in Nanjing district by homogeneous texture segmentation[8][9] and line segment match method[5][6].Obvious, it is a roughly result with some non-road segments and road cracks. Therefore, the original extracted road segments should be organized in combined with the context, and restoring the whole road finally. The powerfulness of markovian framework to organize linear target with contextual knowledge shows earlier in Marroquin[10]and Krishnamachari[11], later, Tupin[12][13] applied it to road organization problem, and it was used firstly in SAR image, but not in complicated high-resolution RS images. The following will illustrate the high-level application in organizing road segments with markovian model to restore the perfect road network.

3.1 MAP-MRF framework

1）Graph definition

In order to explain the road organization problem with MAP-MRF model clearly, a graph is defined at first in the following.

In fig.5, a set of extracted road segments(let us denoted by S_d)are extracted by homogenous texture and line segment match method, in which some belong to the real road and others are false road. Many road segments also remain undetected, we make the assumption that the true road network may be obtained by connecting these detected road segments in an appropriate way and by rejecting the false one. Thus, we add the set S_d' to all possible connections to S_d .a connection is possible if it verifies the following three connections

（a） It links two endpoints of two different road segments.

（b） The distance to be connected is not more than a fixed threshold $D_{\max}$

$$N_i = \left\{ j \in S \,/\, \exists (k,p) \in \{1,2\}^2, M_j^k = M_i^p, j \neq i \right\} \tag{6}$$

（c） Alignment of the two road segments is acceptable.

A new set of segments S is built as the union of S_d and $S_d' : S = S_d \cup S_d'$ .in fig.6 ,these shows the result of the whole road segments and possible connection segments in fig.5. S is endowed with a graph structure, and the graph is denoted by G ,each road segment in S being a node in G ,and two nodes in G being linked by an arc if two road segments in S sharing a common endpoint.

Fig. 5 Extracted road segments with homogeneous texture and line segment match method

Fig. 6 The connected result of fig. 5

In order to define the markov random field in the graph, a neighborhood N_i of node i is given as a set of nodes adjacent to it:

Cliques of the graph G are all subset of road segments sharing a common node, including singletons and cycles of three segments. Furthermore, attributes are attached in graph G, in which a node is associated with a normal length ℓ_i and an arc is associated with an angle R_{ij} between the two corresponding road segments in S.

2) Model

In order to identify nodes belonging to road, i.e., in labeling the graph G, a binary variable L_i is associated with node i. $L_i = 1$, if node i belong to a road segment and $L_i = 0$, if not. With n as the cardinal of G, we can define a label random field $L = (L_1, L_2, \cdots, L_n)$, and L can be taken in 2^n different kinds of configurations.

Given the observation field D (explained in the

$$p(L \mid D) = \frac{p(D \mid L)p(L)}{p(D)} \tag{7}$$

following), the meaning of road organization problem is equivalent to the most probable configuration L, Using bayes rule:

Assume L is a markov random field, as an introduction in section 2.1, we may write:

$$p(L \mid D) \propto p(d \mid l)p(l) \propto e^{\ln(d|l)-U(l)} \propto e^{-U(l|d)} \tag{8}$$

$$p(d \mid l) = \prod_i p(d_i \mid l_i) \tag{9}$$

Where: $U(l) = \sum_{c \in C} U_c(l)$

Considering the independence between nodes of graph G, then:

thus: $$U(l \mid d) = \sum_{i=1}^{N} U(d_i \mid l_i) + \sum_{c \in C} U_c(l)$$

Therefore, the purpose in getting the maximum posterior probability estimation is equal to the choice of the minimum energy. Since the energy function $U(l \mid d)$ is given, this can be solved by simulated annealing algorithm.

3.2 Road segment organization

The main issue is the definition of energy function and the choice of parameter values in energy function according to road organization problem with markovian model. As it is expressed in formula 8, these problems will be illuminated in both the conditional probability energy and the prior probability energy in the following.

1) conditional probability energy

Define the observation field $D = (D_1, D_2, \cdots, D_n)$ deduced from the homogenous texture analysis, and d_i is the mean value of the pixels in corresponding road segment.

$\sum_{i=1}^{N} U(d_i \mid l_i)$ denotes the conditional probability energy while $U(d_i \mid l_i)$ means

the energy in node i. Thus the overall energy in conditional probability is the sum of energy in every nodes. The energy $U(d_i \mid l_i)$ was chosen experimentally after a manual segmentation of roads.

$$U(D_i = d_i \mid L_i = 0) = 0, \quad \text{if } d_i < t_1 \tag{10}$$

$$U(D_i = d_i \mid L_i = 0) = \frac{d_i - t_1}{t_2 - t_1}, \quad \text{if } t_1 < d_i < t_2 \tag{11}$$

$$U(D_i = d_i \mid L_i = 0) = 1, \quad \text{if } d_i > t_2 \tag{12}$$

$$U(D_i = d_i \mid L_i = 1) = 0, \quad \forall\, d_i \tag{13}$$

The parameters t_1, t_2 can be trained by the data of manual segmentation result.

2） prior probability energy

$U(l)=\sum_{c\in C}U_c(l)$ denotes the prior probability energy and C denotes the clique set, this clique energy is chosen to express the following a priori knowledge about roads:

1） Roads are long;
2） Roads have a low curvature;
3） Intersections are rare; accept either ‘cross’ or ‘T’ shapes intersection.

Based on the three assumptions above, we define the following set of energy functions for different cliques：

$$\forall i\in c, l_i=0 \Rightarrow U_c(l)=0 \qquad (14)$$

$$\exists! i\in c / l_i=1 \Rightarrow U_c(l)=K_e-K_l\ell_i \qquad (15)$$

$$\begin{aligned}&\exists!(i,j)\in c^2 / l_i=l_j=1, R_{ij}>\frac{\pi}{2}\\ &\Rightarrow U_c(l)=-K_l(\ell_i+\ell_j)+K_c\sin R_{ij}\end{aligned} \qquad (16)$$

$$\begin{aligned}&\exists(i,j,k)\in c^3 / l_i=l_j=l_k=1, i\,||\,j, i\perp k, j\perp k\\ &\Rightarrow U_c(l)=-K_l(\ell_i+\ell_j+\ell_k)+K_c(\sin R_{ij}+\frac{1}{2}(\cos R_{ik}+\cos R_{jk}))\end{aligned} \qquad (17)$$

$$\textit{in all other cases } U_c(l)=K_i\sum_{i/i\in c}l_i \qquad (18)$$

All parameters express the three previously defined road characteristics. Choosing K_l favors long roads, K_e penalizes extremity, K_c penalizes road configurations with high curvatures and K_i penalizes intersections not fulfilled certain conditions. and K_l , K_e , K_c , K_i are selected between 0 and 1.

After getting the energy function through the above discussion, the optimal label result or the minimum energy can be obtained by simulated annealing method and specific implementation can reference the process of road segmentation method in section2.2.

Now we process the initial extracted road segments in fig.5 with the proposed road organization method, as fig.7 shows the restored result of road network, and the parameters in this using the following values: $t_1=0.6$, $t_2=0.8$, K_l =0.4 , K_e=0.13，K_c=0.35，K_i=0.25.

With the same parameter values in above, this method is applied to another IKONOS image in Nanjing district, fig.8 shows the initial extracted result by homogenous texture and line match segment method, and fig.9 shows the restored result of fig.8.

Fig.7 The restored road network of fig.5 with our method

Fig.8 Another image with some road segments

Fig.9 The restored road network of fig.8

Experimental results show the powerfulness of markovian method to organize road segments, especially in linking road gaps, such as in figs5, 8, there are many cracks and can be linked very well. Meanwhile, false independent road segments can be eliminated according to global optimal energy principle too. as the whole network can be restored from the initial extracted road, it greatly improves common road extraction methods.

3 CONCLUSION

As for the road extraction problem in remote sensing images ,this article illustrates the powerfulness of markovian model at two levels, which includes pixel level application as road segmentation and high level application like road organization. In benefit of markovian model coupled with bayesian method, relative road extraction problems are converted into the Bayesian estimation problem successfully. And experimental results show the powerfulness of markovian method to applications of road segmentation and road organization.

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