A REGION-BASED METHOD FOR GRAPH TO IMAGE REGISTRATION WITH AN APPLICATION TO CADASTRE DATA

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ABSTRACT

Cadastre data can give useful information in certain land use analysis procedures, but these data must be registered to the terrain image. The mis-registration to be corrected is not only due to geometrical deformation or acquisition errors, but also to land use not always following cadastre divisions.

We present two variants of a novel region-based graph matching algorithm which can be used to register a cadastre onto an aerial image. We represent a segmentation of the image as a weighted graph. Its faces are mapped to faces in the cadastre graph, and an optimal mapping is found. We also obtain an indicator of which cadastre edges actually exist in the image. This region-based method strictly follows image edges, but does not always preserve the spatial distribution of the cadastre graph.

1. INTRODUCTION

The Salade analysis system is an ongoing project which aims at segmenting high-resolution images into fields and other large regions with very high reliability. Cadastre data helps by providing additional information about crop distribution and position, but cadastre and image edges rarely match exactly, because land owners do not always follow cadastre limits when growing their crops: A method to register a cadastre graph onto an image is needed.

Cadastre registration is also needed in order to classify whole cadastre regions into land use classes. Without registration, many regions would contain at their edges pixels not belonging to their main class. In addition, the Salade system will be used to update land use databases: Once the initial land use database has been produced using cadastre data, successive runs can use the old land use database as input, instead of the cadastre; it is expected that most edges in the old database and in the current situation match, except for some deformation, which will be corrected by the registration mechanism.

Registration of cadastres to images has been viewed as a non-rigid registration problem [1, and other articles in the same journal issue]. The goal is to find the transformation within a class that best converts an image to a reference image. This approach works when the initial mis-registration is due to sensor deformation, but in our case it is rather due to the two graphs representing data of different nature. We also want the cadastre to register onto image edges as much as possible. More precisely, we want to modify the cadastre graph so that its spatial structure is preserved (that is, the face topology and the face neighborhood relations of its planar representation) while incorporating the geometrical details of corresponding salient edges in the image.

In [2] we presented a method for solving this problem by matching the edges in a cadastre graph to the edges in a *segmentation graph* derived from a multi-scale segmentation of the image. The graph matching itself was solved by simulated annealing optimization of a solution, defined as a mapping between edges in the cadastre graph and chains of edges in the segmentation graph. This method preserves well the face topology of the cadastre graph, but does not always follow salient image edges since auxiliary straight edges must be added to the solution.

In contrast with that edge-based approach, we present here a *region-based* method for solving the same problem. In this method, we represent the salient edges in the image as a weighted graph, the *segmentation graph*. The method works by mapping or labeling each face on the segmentation graph to a face on the cadastre graph. We define an initial mapping, and constraints on mappings which depend on the degree of saliency of edges between faces, and then obtain a near-optimal mapping using an optimization algorithm. We propose two variants, one using probabilistic relaxation for the optimization, and another using simulated annealing. In most graph matching problems [2, 3, 4] two graphs representing the same reality are given, and the goal is to match the edges and nodes that correspond to the same part of that reality. Our method can be viewed as a loose graph matching procedure in which graph faces, instead of edges and nodes, are the primary object being manipulated.

Tests show a 32.0% reduction in the average distance between the cadastre and a ground truth (evaluation procedures are described in section 3), and, more importantly for

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us, the registered portions of the resulting graph follow the edges of the image, so statistical analysis of regions in this graph will be less affected by adjacent regions.

2. THE REGISTRATION ALGORITHM

Both variants of the algorithm work as follows. We first create a graph $\bar{T}$ representing the salient edges in the image (see Section 2.1), including their geometry, and whose edges are weighted according to their degree of saliency. We obtain then its weighted dual graph $T = (E_T, V_T, w)$, with nodes V_T and edges $E_T \subset V_T \times V_T$ (see Figure 1).

We use mathematical morphology operations to remove thin faces from the cadastre $\bar{C}$, and we obtain its dual graph $C = (E_C, V_C)$, whose nodes represent cadastre regions.

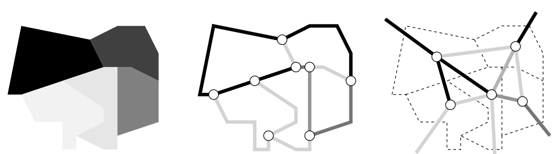

Fig. 1. An image, its segmentation graph $\bar{T}$, and its dual segmentation graph T. Darker edges have higher weights.

Since $\bar{T}$ will be obtained by *over*-segmenting the image, we can assume that each node in T belongs to only one node in C, and formalize a *solution* as a mapping s,

$$s : V_T \to V_C,$$

and use different optimization algorithms to find an optimal or near-optimal solution. We propose two variants: In Section 2.2 using probabilistic relaxation for the optimization process, and in Section 2.3 using simulated annealing.

Throughout this article, $k_0, \ldots, k_6$, β, π_0, π_1, π_2 and π_r are configurable parameters in $[0, +\infty)$; we chose their values empirically, although tests with several parameter sets show that the algorithm is not very sensitive to their values. $N(a)$ is the set of neighbors of the graph node a, and w_{ij} is the weight of the edge in T between nodes i and j.

2.1. Image over-segmentation

To obtain the primal segmentation graph $\bar{T}$, we need the topology and geometry of the salient edges in an image, and a measure of their saliency. A simple method would be to weight each segmentation edge in a watershed segmentation with the module of the image gradient in that edge. However, this measure of edge saliency would be local and single-scale, and therefore not satisfactory, since meaningful structures may appear at different scales of analysis [5].

Several authors have proposed *multi-scale* algorithms to solve this. We use Guigues' *scale-sets* algorithm [6] —because it makes the segmentation criterion and the scale parameter explicit— to obtain a hierarchical segmentation which we flatten as in [2] to get a fine watershed segmentation, with the edges weighted according to how high in the segmentation hierarchy they appear —or how salient they are in the image. We call these weights *apparition weights*.

2.2. Registration by probabilistic relaxation

Probabilistic relaxation or relaxation labeling is an optimization method first proposed by Rosenfeld *et al.*[7]. Following Fu and Yan's notation [8], we define a set of objects to be labeled (the terrain nodes V_T in our case), a set of possible labels (the cadastre nodes V_C), initial probabilities $p^{(0)}$, an influence function d and a compatibility function c.

The influence function d_{ij}, with $i, j \in V_T$, measures the relative influence a face j has over the face i. For non-adjacent faces, it is 0. For adjacent faces, we make it dependent on the area a_j of the face j, and on the length ℓ_{ij} of the edge (i, j). Specifically,

$$d_{ij} = \kappa_i \left(k_0 + k_1 \ell_{ij}^{k_2} + k_3 a_j^{k_4} \right), \quad (1)$$

where κ_i is chosen to fulfill the condition $\sum_j d_{ij} = 1$.

The compatibility function $c_{ij}(\lambda_i, \lambda_j)$, for $i, j \in V_T$ so that $d_{ij} \neq 0$, and $\lambda_i, \lambda_j \in V_C$, measures the compatibility of the labeling $i \mapsto \lambda_i$ and $j \mapsto \lambda_j$, with $0 \leq c \leq 1$ and $\sum_{\lambda_i} c_{ij}(\lambda_i, \lambda_j) = 1$. We have chosen

$$c_{ij}(\lambda_i, \lambda_j) = \begin{cases} (1 - w_{ij})^\beta & \text{if } \lambda_i = \lambda_j, \\ \frac{1-(1-w_{ij})^\beta}{|V_C|} & \text{if } \lambda_i \neq \lambda_j, \end{cases}$$

that is, the more salient the edge between two faces, the better it is these faces be labeled differently.

The initial probability function $p_i^{(0)}(\lambda_i)$, with $i \in V_T$ and $\lambda_i \in V_C$, gives the initial state of the system (a sort of fuzzy initial solution). It should reflect the *a priori* probability that i is mapped to λ_i. Note that probabilistic relaxation works correctly even if these are not real *a priori* probabilities obtained through statistical analysis. We chose the following initial probabilities: For each node i in T, we find the center of gravity b_i of its corresponding face in $\bar{T}$. We then find the face in $\bar{C}$ whose center of gravity is closest to b_i, and its corresponding node in C, c_i. We define

$$p_i^{(0)}(n) = \begin{cases} \alpha_i \pi_0 & \text{if } n = c_i, \\ \alpha_i \pi_1 & \text{if } n \in N(c_i), \\ \alpha_i \pi_2 & \text{if } n \in \cup_{b \in N(c_i)} N(b) \setminus \{c_i\}, \\ \alpha_i \pi_r & \text{otherwise} \end{cases} \quad (2)$$

with α_i such that $\sum_{\lambda_i} p_i^{(0)}(\lambda_i) = 1$.

An iterative process is then run, repeatedly updating the current probabilities with an update function defined in [8],

$p^{(t+1)} = F(p^{(t)}, c, d)$, until convergence (or for a maximum number of iterations). The solution is then the labeling

$$s^{(\infty)}(i) = \operatorname*{argmax}_{\lambda \in V_C} p_i^{(\infty)}(\lambda).$$

In our implementation, we treat values of $p_i^{(t)}(\lambda)$ lower than a small threshold as 0, which greatly reduces processing time without changing the results.

2.3. Registration by simulated annealing

Simulated annealing is a well-known heuristic optimization algorithm that can find near-optimal solutions for problems where steepest-descent-based optimizers tend to get stuck at local optima. To use it we need an initial solution $s^{(0)}$, a way of evaluating the *energy* of a solution, and a way of obtaining solutions similar to a given solution. Starting from $s^{(0)}$ the algorithm iteratively modifies it to obtain a near-optimal solution $s^{(\infty)}$.

To obtain $s^{(0)}$ we use $p^{(0)}$ defined in Equation 2: $s^{(0)}(i)$ is chosen randomly following the probability distribution given by $p_i^{(0)}$. To obtain from s a similar solution s', we replace a certain number of its labelings; each new labeling $s'(i)$ is chosen randomly following $p_i^{(0)}$.

To evaluate the quality of a solution s, we do the following. For each $i \in V_T$, we find $e_s(i)$

$$e_s(i) = a_i^{k_5} \cdot \sum_{j \in N(i)} e'_s(i,j)$$

$$e'_s(i,j) = \begin{cases} d_{ij}\left(1 - (1 - w_{ij})^{\beta}\right) & \text{if } s(i) = s(j), \\ d_{ij}(1 - w_{ij})^{\beta} & \text{if } s(i) \neq s(j) \end{cases}$$

where a_i is the area of the face in $\bar{T}$ corresponding to the node i in T, and d_{ij} is as defined in Equation 1. The energy of a solution s, $E(s)$, is the sum of the e_s of its nodes, plus a penalty for each node that has no neighbor labeled like itself. If there are d such nodes, $E(s) = k_6 d + \sum_{i \in V_T} e_s(i)$. The lower the energy, the better the solution.

2.4. Post-processing

The output $s^{(\infty)}$ of any of these optimization algorithms is then processed in several ways.

First, each node n which has no neighbor labeled like n, is merged to the neighbor node $n' \in N(n)$ for which the edge $(n, n') \in E_T$ has the lowest apparition weight w.

Second, following the mapping defined by $s^{(\infty)}$, the connected faces in $\bar{T}$ which have the same label are merged. The resulting primal graph $\bar{R}$ is taken as the registration of the cadastre graph $\bar{C}$ onto the image.

Each edge e in $\bar{R}$ is the concatenation of a certain set of edges $P(e)$ in $\bar{T}$. We compute $m(e)$, the average of the apparition weights of the edges in $P(e)$, weighted by their lengths. This gives a measure of how strong the image edge corresponding to a registered cadastre edge is. Low values indicate that there is probably no corresponding image edge.

3. EXPERIMENTS AND RESULTS

We have run both variants of the algorithm, using several sets of parameters, on a test site of $4\,\text{km}^2$, on which we defined a ground truth. We let both optimizers run for about 4 minutes. The segmentation was computed from the RGB image layers, downsampled to $2\,\text{m}/\text{pixel}$ to improve speed. In future work we plan to also use texture information and region shape for segmenting.

We drew the registered cadastre graph and the ground truth, and computed the average distance between pixels in the rasterized cadastre graph and pixels in the ground truth. We excluded from this average those cadastre edges for which the average distance to the ground truth was larger than 6 m, or which had a pixel that was farther than 20 m away from the ground truth —these *non-matchable edges* probably do not have a corresponding image edge. We calculated the average distance between the *unregistered* cadastre graph and the ground truth in the same way.

The results for the best parameter set are summarized in Table 1 (*length* does not include non-matchable edges). Figure 2 shows results for the probabilistic relaxation procedure for a $1\,\text{km}^2$ region.

	unregistered	registered relaxation	registered annealing
area	$3.993\,\text{km}^2$	$4.233\,\text{km}^2$	$4.045\,\text{km}^2$
length	63.2 km	85.6 km	125.5 km
mean distance	2.346 m	**1.594** m	**1.855** m
iterations		1000	15000

Table 1. Evaluation results.

The algorithm successfully registers the cadastre onto the image, and with the best parameter set it reduces the average distance between the cadastre graph and a ground truth from 2.346 m to 1.594 m, 32.0% less. The resulting graph is registered onto the segmentation edges, hence onto salient edges in the image —statistical analysis of these regions will be less affected by adjacent regions.

The choice of parameters affects the result, but not critically. For example, 72 different parameter sets give mean distances between 1.594 m and 1.869 m for relaxation, and between 1.855 m and 2.126 m for annealing.

4. DISCUSSION AND CONCLUSION

Our requirements were that the spatial distribution of the cadastre had to be preserved as much as possible, and the

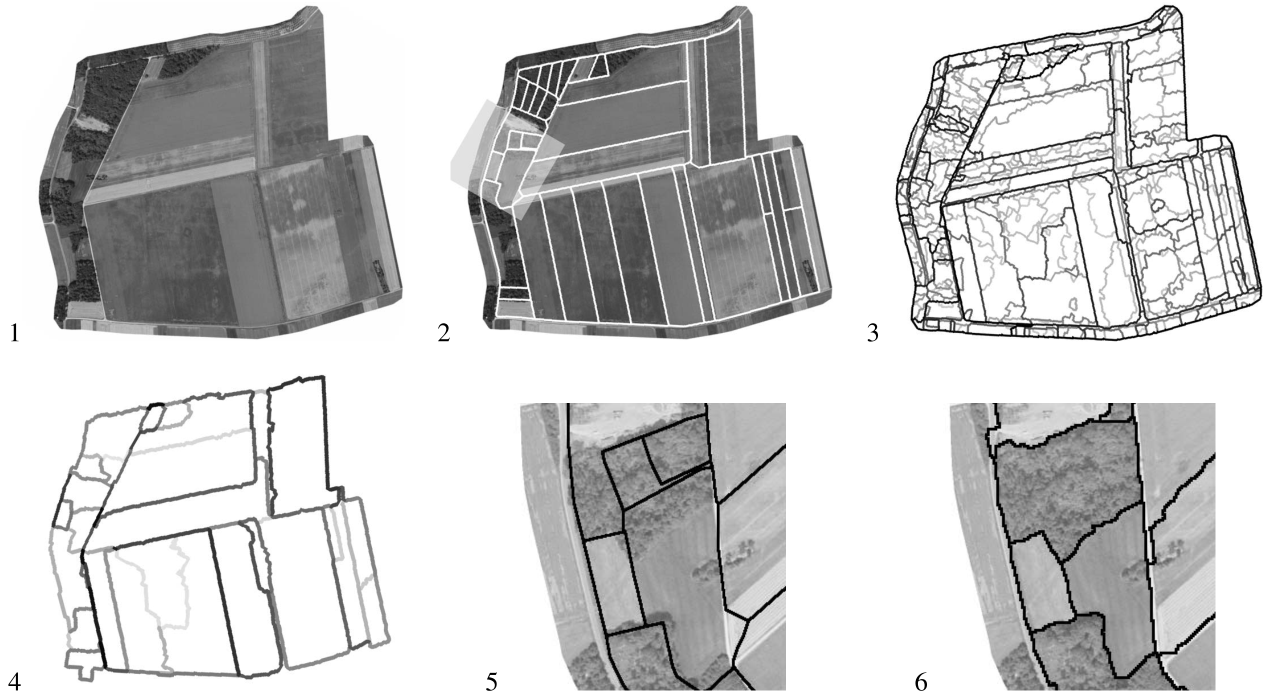

Fig. 2. Results for a portion of the test site. Source image (1); cadastre graph $\bar{C}$ (2, boxed area is shown enlarged in 5 and 6); segmentation graph $\bar{T}$ (3, darker edges have higher apparition weights); registered cadastre (4, darker edges have higher values of m); close-up on the unregistered (5) and registered (6) cadastre.

geometrical details of the image had to be transferred to the cadastre graph. Both variants succeed well in the second goal since their output only contains edges from the segmentation graph, and strong edges are followed more than weak edges.

However, while the general spatial distribution of the cadastre graph is preserved, both algorithms add, remove, split and merge cadastre faces. Relaxation adds less extra faces than annealing, which accounts for its better score. These changes actually follow what happens in the image, so it is not clear that they are errors.

Visual inspection shows that the measure $m(e)$ (Section 2.4) does indicate if a cadastre edge actually exists in the image. We will use this information to merge cadastre regions containing the same crop.

We should compare this algorithm to the previous one described in [2]. The edge-based algorithm preserved the spatial distribution of the cadastre graph much better, at the cost of adding auxiliary edges that did not correspond to image edges. These region-based algorithms, on the other hand, strictly follow image edges, at the cost of not always preserving spatial distribution. Although numerical evaluation gives better figures for the region-based algorithms, for a given application the trade-off between geometrical precision and topology preservation should be taken into account.

5. REFERENCES

[1] A. Goshtasby et al., "Nonrigid image registration," *Computer Vision and Image Understanding*, vol. 89, no. 2/3, pp. 109–113, Feb./Mar. 2003.

[2] Roger Trias-Sanz, "An edge-based method for registering a graph onto an image [...]," Tech. Rep. 2004/1, SIP-CRIP5 and IGN, http://recherche.ign.fr, Mar. 2004.

[3] C. Hivernat and X. Descombes, "Mise en correspondance et recalage de graphes," Tech. Rep. RR-3529, INRIA, http://www.inria.fr, Oct. 1998.

[4] S. Gautama and A. Borghgraef, "Using graph matching to compare VHR satellite images with GIS data," in *Proc. IGARSS 2003*, July 2003.

[5] D. Marr, *Vision*, Freeman and Co., 1982.

[6] L. Guigues et al., "Scale-sets image analysis," in *Proc. ICIP 2003*, Sept. 2003.

[7] A. Rosenfeld et al., "Scene labeling by relaxation operations," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 6, pp. 320–433, June 1976.

[8] A. Fu and H. Yan, "A new probabilistic relaxation method based on probability space partition," *Pattern Recognition*, vol. 30, no. 11, pp. 1905–1917, 1997.