DETECTING CHANGE IN ROAD NETWORKS USING CONTINUOUS RELAXATION LABELING

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ABSTRACT:
In this paper we examine a system based on computer vision for automated detection of change and anomalies in GIS road networks using very high resolution satellite images. The system consists out of a low-level feature detection process, which extracts road junctions, and a high-level matching process, which uses graph matching to find correspondences between the detected image information and the road vector data. The matching process is based on continuous relaxation labelling. It is driven by spatial relations between the objects and takes into account different errors that can occur. The result is an object-to-object mapping between image and vector dataset. The mapping result can be used to calculate a rubbersheeting transformation which is able to compensate for local distortions. A measure of change is defined based on the number of null assignments. We show how combined with a condition to characterize acceptable errors this measure is useful and reliable to characterize inconsistencies between image and vector data.

1. INTRODUCTION

A major challenge in the production and use of geographic information is assessment and control of the quality of the database. The rapid growing number of sources of geospatial data pose severe problems for integrating data. One of the major challenges for content providers to face is the problem of upgrading their current databases to a higher accuracy and ensuring the quality of the information. Current techniques cannot support this in a cost-effective way due to the necessary manpower. Automated detection of change and anomalies in the existing databases using very-high-resolution (VHR) satellite images can form an essential tool to support quality control and maintenance of spatial information.

The main problem to address is the difference in data representation. To be able to compare geospatial vector data with images, the information in the images needs to be described in terms of object features. Automatic detection of man-made objects however is a difficult problem. Shadow, occlusion and variety in appearance all give rise to a fragmented and imprecise description of the image content, especially if consistent detection is required over large datasets. Making a reliable statement about the quality of the GIS data requires knowledge about the performance of the different object detection techniques. Our focus is the development of such reliable and predictable techniques. Rather than producing results on a selected number of images, we wish to be able to characterize the performance of the detection. This performance characterization is an essential step towards reliable tools within an operational environment.

The proposed system for change detection is based on feature based spatial registration, where detected features in the image are registered to corresponding features in the vector data. The system consists out of two stages: 1) a low-level feature detection process, which extracts roads and junctions using an improved ridge detector, and 2) a high-level matching process, which uses graph matching to find correspondences between the detected image information and the road vector data. The graph matching process, based on continuous relaxation labeling, is driven by the spatial relations between the features and takes into account different errors that can occur (e.g. spatial inaccuracy, data inconsistencies between image and vector data). The matched features can be used to calculate a rubbersheeting transformation between image and vector data, using triangulation. Such a transformation is able to compensate for the local distortions that can occur between the datasets. Additionally can the object-to-object mapping be used to define measures of change between datasets.

2. IMAGE BASED CHANGE DETECTION

Feature based registration is the primary approach to compare data sources that have differing types of representation as is the case for images compared to vector data. Traditional pixel based correspondence techniques are inadequate to solve this registration problem (Brown, 1992). An additional processing step is necessary to convert the raw image information to a representation, which is closer to the vector data. This is done by detection of image features like lines, corners and segments. Given these features an abstract representation can be build as an attributed graph (Diestel, 1997). The graph nodes represent image features and the node attributes can contain measurements on these features. The graph arcs represent relations between features and the arc attributes can contain measurements on spatial relations. A similar graph can be build on the vector data, using vectors as nodes and relations between vectors as arcs. The problem of registration is represented as a graph matching problem, which seeks the correspondence of similar nodes between two attributed graphs.

In computer vision error tolerant graph matching techniques form an important class of techniques. These techniques seek a graph or subgraph morphism, which allows for distortions. A general distortion model defines the deletion and addition of graph nodes and arcs, and replacement of attribute values. A similarity measure or distance function between two graphs is used that models the occurring distortions using heuristics. Early techniques were a generalization of string matching. More recent models are based on information theoretic principles or Bayesian modeling. Solving the correspondence problem is difficult and several optimal and approximate techniques have been proposed. These include among others search trees, dynamic programming, annealing and genetic algorithms. We examine relaxation labeling, a popular approximate technique which has low, polynomial time complexity.

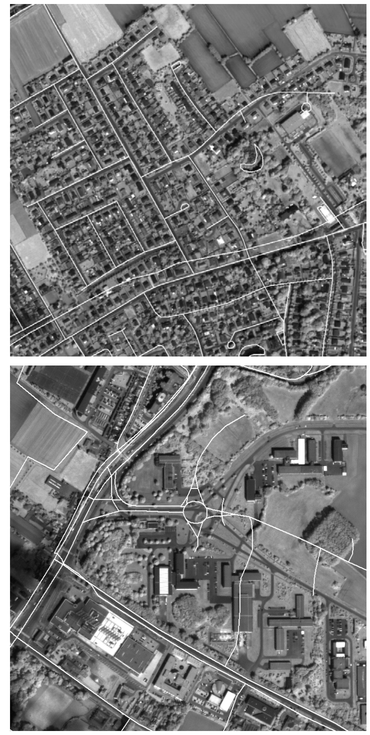

Figure 1. Examples of the image with the road vector data in overlay

Figure 2. Detection of junctions. Crosses are junctions after verification

3. ROAD JUNCTIONS AS REGISTRATION OBJECTS

The road network that can be detected using a road detection scheme is often not of sufficient quality to be useful for comparison with a road database. The main difficulty is the difference in representation between the pixel chains that can be detected from the image and the polyline vectors that represent roads in the database. This difference makes it difficult to reliably compare the information in the image with the database. More robust image objects are necessary. We found road junctions to be good candidates since in their abstract form, they can be represented as point objects both in the image as well as in the database.

We model a road junction as a point where lines meet. This means that built upon the road network that is detected using ridge detection, we look for pixels in the pixel chains which have three or more neighbors. We choose this strategy above corner detection, because corner detection gives many spurious responses not belonging to junctions that are not easy to filter out. Our method stays closer to the road network logic. A major problem however is that the detection of the road network fails in the vicinity of road junctions since the ridge model does not hold anymore. At the junction, the intensity surface will not be modeled as a valley or a ridge but as a flat spot. As a consequence, the road network will often be broken around road junctions.

We implemented a simple region growing scheme (Gautama, 2002) which extends the initial road fragments with regions which show a similar gray value. For roads which are adequately detected, this proves to be sufficient in many cases to bridge the bad spots at road junctions. The simple scheme is of course not foolproof. A cheap and efficient verification to filter out false alarms is to check if in the vicinity of a hypothetical road junction a flat spot exists. Junctions are seen by the ridge detector as a flat region. By simply applying different thresholds on the gradient and the curvature, which have already been calculated for the detection of lines, we can detect the flat spots and verify our road junctions. Fig.2 shows an example of junction detection. The boxes are detected road junctions using the neighbor model. Crosses are junctions which are verified and retained using the flat spot check.

4. FINDING CORRESPONDING OBJECTS USING GRAPH MATCHING

In the previous section, junctions were found to be stable registration objects. The problem can be represented as finding the correspondence between two sets of points: one set originating from the image and one set which can be extracted from the database. This can of course be generalized to situations other than image-to-GIS registration, like image-to-image or GIS-to-GIS.

4.1 Continuous relaxation labeling

The matching problem can be defined as a graph labeling problem. The following are defined:

- a set of objects *i*, corresponding to image features;
- a set of labels λ_i, corresponding to GIS features;
- a neighbour relationship over the objects;
- restrictions on possible labels between pairs of neighbouring objects.

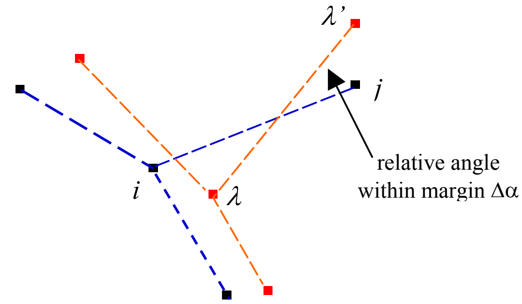

Figure 3. Relational binary constraint.

Relaxation labeling techniques use an iterative process to determine the probabilities of each object. Different update rules have been proposed. In (Hummel, 1983) the relation between different update rules is analytically shown. The problem of finding consistent solutions is shown to be equivalent to solving a variational inequality which is based on the mathematical concept of "consistency". This concept is interesting because it lays bare the foundations of the labeling process and offers guidance in determining good compatibility coefficients.

To each object *i* a probability distribution $\vec{p}$ is associated that *i* has label λ_k, $(p_i(\lambda_1),\dots p_i(\lambda_m))$:

$$0 \le p_i(\lambda_k) \le 1, \quad \sum_{k=1}^{m} p_i(\lambda_k) = 1 \qquad (1)$$

For each pair of neighbouring objects *i* and *j* and for each pair of labels λ_k and λ_l, a compatibility coefficient $r_{ij}(\lambda_k,\lambda_l)$ exists. These coefficients express the compatibility of assigning label λ_k to object *i* in combination with assigning label λ_l to object *j*. Negative values express incompatibility, positive values compatibility. Given these quantities, the support of a label λ_k for the object *i* given by the correspondence $\vec{p}$ is defined by

$$s_i(\lambda_k) = s_i(\lambda_k,\vec{p}) = \sum_{j=1}^{n}\sum_{l=1}^{m} r_{ij}(\lambda_k,\lambda_l)\, p_j(\lambda_l) \qquad (2)$$

To find a consistent labeling, we optimise the average local consistency, given by

$$A(\vec{p}) = \sum_{i=1}^{n}\sum_{k=1}^{m} p_i(\lambda_k)\, s_i(\lambda_k,\vec{p}) \,. \qquad (3)$$

This is a quadratic function which we optimise using a constrained gradient descent method, taking into account the restrictions of Eq.(1).

To take into account the possibility that an object i does not have a correspondent, the set of possible labels and the associated distribution $\vec{p}$ is extended with a null label $\lambda_\varnothing$ and probability $p_i(\lambda_\varnothing)$. As each object i can be mapped on the null label, a small negative weight w^0 should be assigned to the compatibility coefficient $r_{i\varnothing}(\lambda,\lambda_\varnothing)$ to avoid that a full null mapping comes out as the most consistent solution. In (Gautama, 2003), it is shown that the value for this weight is controlled by a simple condition:

$$(1-f^0)w^0 < f^- w^- \quad (4)$$

where f^- and f^0 are the fraction of incompatible and null assignments in the neighbourhood of object i. This condition can be used to determine the weights for the compatibility matrix given the expected graph error. It allows to make a distinction between distortions which should find a correspondent in the other dataset, and large changes which should be assigned the null label.

4.2 Matching sets of points

Relaxation labelling is a generic technique to solve constraint satisfaction problems. To apply this technique to matching sets of road junctions, we need to introduce the constraints which apply to the system. Several options exist:

1. the number of road arms should be the same for corresponding junctions;
2. interconnecting roads between pairs of corresponding junctions should be the same;
3. geometric invariants under a given spatial transformation between subsets of corresponding junctions should be preserved.

The initial detection of roads that can be achieved is not of sufficient quality to use the first two options as information for the correspondence process (Gautama, 2002). Fragmentation and false detections can frequently occur in the detected road network and are difficult to control. We therefore opt to use geometric invariants between subsets of corresponding junctions. The most simple constraints are binary relations like geometric relations (e.g. angle, distance) between a junction and its neighbours to find correspondences. These are much more stable features given the detection quality which we can realistically expect from road detection. In these experiments we rely only on the relative angle between pairs of points. Fig.3 shows

Figure 4. Result of registration process using rubbersheeting transformation.

an illustration of this constraint. The black points show object points i and the grey points show the label points λ. In mapping a pair of points i and j on λ and λ' the relative angle between the lines ij and $\lambda\lambda'$ should lie within a margin $\Delta\alpha$. (e.g. $\pi/4$). If this constraint is violated, the compatibility coefficient $r_{ij}(\lambda,\lambda')$ is assigned a negative weight w_r.

4.3 Experimental results

For our experiments we investigate the automatic registration of the IKONOS image of Ghent with a road vector database. The image is a standard pan-chromatic GEO product. An extract of the region of the vector data is shown in Fig.1. This figure also shows examples of the IKONOS image in overlay and illustrates some of the problems that can occur. Although the observed terrain is flat, relatively large inconsistencies exist between the two data sources. In addition the database that was used, did not contain an explicit junction class. We have taken the feature points describing the break points of the vector polylines as junctions. For the region under examination this approximates the junctions in the scene since the region contains mainly straight streets. A number of spurious points is falsely introduced in the vector set of points, due to points which do not belong to junctions (e.g. points defining a roundabout). These points however were left in the dataset as additional source of noisy structures.

Using the detected junctions in the image and the set of feature points from the vector data, relaxation labeling was applied to find the corresponding junctions in the two datasets. The image dataset contains 82 points, the vector dataset contains 205 points. The correspondent of each image point is searched within a radius of 150m around the position of the image point in the vector dataset. In our case, this amounts to an ambiguity of around 10 candidate vector points per image point. By performing a manual registration of the image points with the corresponding vector points, we calculated an RMS of 7 meter with a maximum error of 50 meter. The parameters of relaxation were set at $\Delta\alpha$=11.25°, $w^r=-0.5$, $w^0=-0.1$. This allows for a relational error $f=20\%$, as in this example the image dataset contains no spurious points, meaning $f^0=0\%$. After convergence of the relaxation labelling process, we obtain 71 correct correspondences, 11 null correspondences and no false correspondences.

Based on the matched points, a rubbersheeting transformation can be performed. This transformation performs a triangulation of the image set of points and calculates a local affine transformation of each image triangle to the corresponding triangle in the vector data. In this way, local distortions can be compensated, which is not possible if a global transformation would have been used. Fig.4 shows the result of the registration process.

5. DETECTING CHANGE USING MATCHED OBJECTS

Whereas global transformation schemes (GTS) look for the best global transformation which optimizes the mean error between two sets of points, graph matching searches directly for the best object-to-object mapping that satisfies all local constraints. This makes graph matching more suited for change detection since local constraints are able to more finely characterize the correspondence of points than the total mean error. Fig.5 illustrates the basic problem. A fragment is shown containing the image road junctions and the vector road junctions, represented by resp. crosses and circles in the image. The two datasets, of which a small extract is shown, have been registered using the best affine transformation after manual registration. The mean error has been minimalized but due to inconsistencies reasonable errors remain present even after registration.

A standard practice is to select for each feature point the nearest corresponding point in the other dataset. This correspondence is shown by the solid white arrows. This example shows that the distance between points, which is implicitely used by global

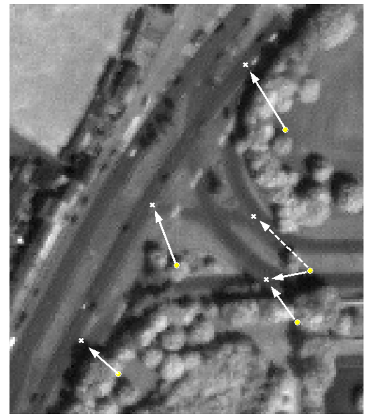

Figure 5. Illustration of the problem in using distance as correspondence criterium.

transformation schemes in the error function to be optimized, is not always a good criterium to select corresponding points. It is adequate to calculate the affine parameters since these distortions have a minor impact on the calculation if enough points are used. Graph matching in this case is able to find the correct correspondence since the error that is made in the previous case violates the local constraints. The correct correspondence is shown by the dashed arrow.

The main difference between GTS and graph matching however lies not in the mistakes that are made but in the mistakes that can be ignored. To illustrate the difference a test area has been chosen containing 77 road junctions in both datasets. Selected parts of the data show severe inconsistencies while the overall consistency is adequate. The mean RMS calculated after performing a manual registration using all 77 points is m_d = 21 meter.

Relaxation labeling was performed on this data, using the same parameter set $\Delta\alpha$=11.25°, $w^r=-0.5$, $w^0=-0.1$. The result after convergence is summarized in Table 1. It shows a reasonable detection rate of 59.8%. More important however is the small number of false detections, namely 2.6% or two points out of 77, which is important with respect to reliability. The condition in Eq.(4) makes it possible to predict when a null label will be assigned. Namely, a vector junction is mapped on the null label if it shows a relational neighbourhood error larger than 20% when compared to the neighbourhood of the best corresponding point. With respect to change detection this means that in the absence of spurious points, the number of null assignments can be used as a (negative) measure of the quality of the vector data. This measure is useful in addition to mean distance measured in the object-to-object mapping. As more null assignments occur, more junctions can be expected to have a relational error larger than 20%. Fig.7 shows a detail of the matching result. The crosses on the image show the location of the image junctions. The white squares show the vector junctions which are correctly mapped with a line drawn to the corresponding image junction. The white triangles show the false positive correspondences. The black circles show the null labels. The example shows a concentration of null labels in the area of the roundabout where severe inconsistencies exist between image and vector data.

The same data was processed using GTS, where correspondences based on distance were accepted using a threshold $T_d = m_d$ and $T_d = 2* m_d$. The performance in table 1 shows a high false detection rate of 23.4% (18 points out of 77) which remains unchanged even after reducing the distance threshold T_d. The same argument as explained in Fig.5 holds in this case. Due to the large number of false positives, the number of null assignments is not usable as a measure of change in the case of GTS. In addition, due to the false positives will the mean distance be an unreliable measure of change.

	Positive	false positive	Null
RL	59.8%	2.6%	37.6%
GTS $T_d = 42$ m	71.4%	23.4%	5.2%
GTS $T_d = 21$ m	49.4%	23.4%	27.3%

Table 1. Matching performance.

6. CONCLUSIONS

In this paper we discussed for automated detection of change and anomalies in GIS road networks using very high resolution satellite images. The system uses graph matching to find correspondences between the detected image information and the road vector data. We have shown how spatial relations between objects can be used to find a reliable object-to-object mapping. The mapping is useful to define a measure of change based on the number of null assignments. This measure is more reliable for detecting change when compared to global transformation schemes.

Figure 6. Matching result using relaxation labeling.
(square=correct, circle=null, triangle= wrong).

7. REFERENCES

Brown L.G. (1992). A Survey of Image Registration Techniques. ACM Computing Surveys, Vol. 24, No. 4, pp.325-376.

Diestel R. (1997). Graph Theory. Springer-Verlag, New York.

Gautama S., Borghgraef A., Bruyland I. (2002). Automatic registration of satellite images with GIS databases. Proc. Advanced Concepts for Intelligent Vision Systems ACIVS 2002, Gent, Belgium. 7 pag.

Gautama S., Borghgraef A. (2003). Using graph matching to compare VHR satellite images with GIS data, Proc.IEEE Intl. Geoscience and Remote Sensing Symposium IGARSS 2003. Toulouse, France. 3 pag.

Hummel R., Zucker S. (1983). On the foundations of relaxation labeling processes. IEEE Transactions on Pattern Analysis Machine Intelligence, Vol.5, No.3, pp.742-776.

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