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PROBABILISTIC MATCHING OF MAP OBJECTS IN MULTI-SCALE SPACE

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ABSTRACT

Nowadays, multiple scale geo-databases have been building with NSDI and one key task focuses on continuous updating. Based on foundational map patterns and specifications, the corresponding relationships between different scale maps are established to reflect their relative functions. This paper presents the methodology and implementation for automatic object match between two neighbor-scale maps. The approach uses the buffer overlay to generate two sets of candidate corresponding objects, and applies multiple-measure probabilistic match to identify the explicit correspondent object with the largest likelihood. Through table join many-to-many corresponding relationships can be determined. Detail analysis about the matching results are given and discussed in two maps of one same region with neighbor scales. The aim of map match is to find the corresponding objects in the source database, and propagate them to target-scale map and update the matched spatial objects with them, which provides a novel way to update the scale-linked maps automatically.

KEY WORDS

Data matching, multi-scale map, probabilistic method

1 BACKGROUND AND OBJECTIVES

1.1 INTRODUCTION

Nowadays, multiple scale spatial databases are built with the NSDI, and map data updating online or offline among multi-scale databases become an onerous and cumbersome task. But if the corresponding relationships of objects among multi-scale maps are built, the cascade-scale map updating can be implemented efficiently and effectively from one scale map to another scale-linked map.

To build the corresponding relationships among multi-scale map objects, many factors must be taken into account, including model generalization, map structure or morphology information, as well as the geometric, topological and semantic attributes.

Although multi-scale maps are the representation of geographic area with different spatial-temporal scales, they focus on the same geographic entities or phenomena. It means the same or evolutionary geographic features in the same place are showed in different representations according to cognition and abstraction. It is the premier foundation of the similarity match between two neighbor-scale maps. Although two maps are similar from the holistic view, they may have different spatial patterns and morphologies, and the number of the spatial objects and their relationships may be heterogeneous. So the critical task is to determine the similarity between the objects in two neighbor-scale maps, match them and find the link relationship between them. These approaches are the key techniques to implement the updating of scale-linked maps.

The paper is organized as follows. Related work about similarity and match of map objects are stated in section 1.2. The relationships of multi-scale map objects are analyzed in section 2.1 and the concrete details and procedures of probabilistic match are delivered in section 2.2. The implementations with test maps and result analysis are manifested in section 3, and the concluding remarks are presented in section 4.

1.2 RELATED WORK

Map matching is defined as the process of correlating two version sets of geographical positional information. Holt and Benwell (1997) define spatial similarity as those regions, which at a particular granularity (scale) and context (thematic properties) are considered similar. From the psychological and cognitive viewpoint similarity of the two space scenes are analyzed (Nedas and Egenhofer,2008), but it needs explicit domain knowledge about spatial objects and their relations for the relaxation of spatial query constraints. Spatial similarity assessment (Rodríguez and Egenhofer, 2003; Rodríguez and Egenhofer, 2004) are designed to retrieve and inflate spatial information between two space scenes. And the similar match among different databases helps to build the inner connections and find the difference to distinguish the change and to update or fusion spatial data.

Similarity-matching methods based on geometric model emphasize the similarity theory and depend on the vector cross of spatial point pairs (Nedas and Egenhofer, 2003; Goldstone, 2004). Jones et al. (1999) present methods for change detection using polygon area-class maps in which the reliability of the result is assessed using Bayesian multivariate and univariate statistics. Yan (2010) discusses spatial similarity relationships in details in multi-scale spaces. Based on theories for reasoning with topological, metric, and directional relationships several computational models for spatial similarity have been developed (Li and Fonseca, 2006). But these analysis are almost based on two simple objects, such as line-line, line-face. If the space scenes or datasets include more than three objects or group objects, the process may fail to handle.

Geometrics, thematic attributes are the three principle properties of map objects, and the similarity match among the objects should be analysed firstly. Geometric location is the most foundational factor of the geographic feature, and the geometric shape manifests its location and form. Thematic attributes deliver the natural and thematic properties to help human understand them with qualitative and quantitative description, such as classification and reasoning (Janowicz et al., 2008).

In multi-scale map space, the matching becomes the comparison of the objects to identify the corresponding relationships between two version maps, and the automatic updating of cascade-scale map depends on the implementations of these matches. A novel approach called incremental updating in multi-scale space has been developed (Kilpeläinen and Sarjakoski, 1995; Anders and Bobrich, 2004; Ying et al., 2009). In the procedures, the master database provides the newest spatial data and the corresponding relationships are built, then the updating is propagated to the target database. According to this idea, Harrie and Hellström (1999) created a prototype system that propagated updates of roads and buildings from the master to the target dataset. Their conclusion was that a multiple representation database enables analysis using several scales and ensures consistency between datasets defined at different resolution.

Whether similarity match between two space scenes or two version datasets, most methods focus on the match of the one-one relationship, and have troubles to deal with group objects. But for multi-scale map, only the many-to-many correspondence can reflect the reasonable relationships of the group objects between neighbour-scale maps because of cartographic generalization. Thus, to identify the multiplicity between the objects in neighbour-scale maps become the vital mission in the procedures of updating the cascade-scale map.

2 APPROACH & METHODS

2.1 MATCH ANALYSIS IN MULTI-SCALE MAP SPACE

In multi-scale map space, many operators of map generalization are executed to control the information content/entropy and to keep map legibility. Therefore, the representations of the same geographic region are different in different scales. The differences embody many aspects, like the quantity, form, configuration and distribution of map objects.

At the first place, the geometric shape and location of the same objects or phenomena may have tiny deviations or changes with the operators of map smoothing, simplification, exaggeration, displacement according to the different accuracy at different map scales. Object match in multi-scale map space needs to tolerate and accept the locative deviation and distinguish the identical or similar geographic objects from different objects. In most cases, this link relationship is 1-1 correspondence as table 1 showed.

Furthermore, there are many objects are deleted/selected in the lower resolution map with the operators of selection of objects from the finer resolution map, which means there is no corresponding object with each other between two neighbor-scale maps. In these circumstances, the corresponding relationship is 1-0 or 0-1 cardinality as examples in table 1. More important corresponding relationship is many-to-many (M-N) correspondence between two group objects. The operators of aggregation, mergence and decomposition/collapse in map generalization cause group objects to change their distribution and layout, as well as the typification / regroup of buildings and residence areas as table 1 showed. During these processes, group objects are reshaped and regrouped in another scale map, which results in complicated corresponding relationships. The multiplicity of objects match in multi-scale map spaces is the key and most difficult techniques in the process of automatic updating propagation.

In addition, the classification and semantics have similar information among the multi-scale map spaces as the result of objects' aggregation and mergence /re-classification with new map specifications. Therefore, the semantic match may not identify consistence as the same in the uniform map specification.

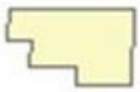
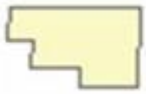
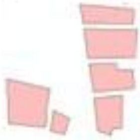
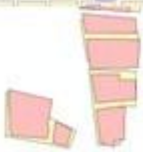
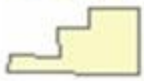
From above discussion, it is evident that objects matched in multi-scale space have their own characters, and the paper will develop the probabilistic method to determine the similarity between them, especially cope with many-to-many corresponding relationship, with the consideration of factors about map objects and multi-scale space.

2.2 PROBABILISTIC MATCHING PROCESS

2.2.1 RELATED WORK

In multi-scale map space, two neighbor-scale maps have the same or similar specifications and schemas, which results that the spatial pattern and format have many similarities. Therefore, map objects have the comparability between the multi-scale maps. Generally, most features are organized by map layers in database. Here we use the up-to-down method (Ying et al., 2009). The mainly workflow is illustrated in figure1.

Table.1 Generalization operators and correspondence cardinality between two maps with examples

#of objects in L	#of objects in S	cardinality	Object(s) in L	Object(s) in S	overlap	generalization factor
1	0	1-0				deletion
1	1	1-1				selection
1	N	1-N				Decomposition /collapse
M	N	M-N				Typification /regroup
0	1	0-1				new born
N	1	N-1				Aggregation /mergence

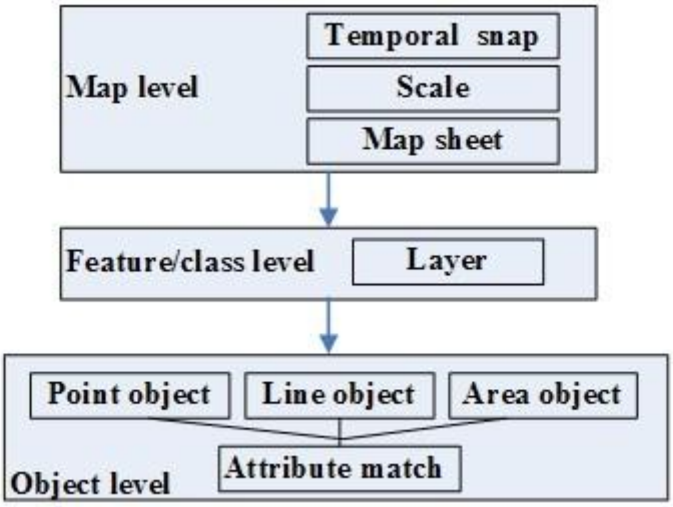


Figure.1 Workflow of matching process of multi-scale maps

The matching process starts with one object in one scale map and try to determine a set of possible corresponding objects in another scale map. The candidate objects must belong to the same or similar feature class before comparison. We call it class match in feature level, which means that the two candidate datasets must have the same feature content during the match, such as road, resident, hydrology. Obviously, the object in one class cannot change to another class, for example, from the road to the water.

It is the common principle that multi-scale maps represent the same real-world entities or the phenomena at the same geographic location. The objects within two neighbor-scale maps must have inner connections, and object matching attempts to find the corresponding cardinalities. Generally, spatial objects are compared with each other through semantics, geometric and topological aspects to determine the difference. For line object and map, there are many approaches and algorithms to deal with these problems, such as buffer analysis (Mantel and Lipeck, 2004; Fu et al., 2008; Ying et al., 2007; Ying et al., 2008), hausdorff distance, probabilistic statistics (Jones et al., 1999; Tong et al., 2007; Walter and Fritsch,1999). The paper will integrate the probabilistic match with geometric and thematic attributes to determine the bilateral relationships between two neighbor-scale maps.

2.2.2 MEASURES SELECTION

The measures in the matching process include spatial and non-spatial parameters. As the above discussed geographic location and geometric shape are the primary references to produce the candidate sets. Moreover, the factors involve distance, metric shape, direction, structure and topology. Except for the distance between two points, hausdoff and deviation distance are utilized between two polylines; also the centroids of shape can be calculated to measure the distance between two areal objects.

Noticeably, the distance measure could merely constrain spatial objects along one dimensionality. So other non-spatial measures are adopted to enhance the matching probability; thematic attributes and name are mainly the parameters in the non-spatial indicators. The main measures used in this paper are listed in table 2. Taking the complexity of areal objects into consideration, the paper will take them as examples.

Table.2 Multiple measures about map objects

	Distance	*Centroid distance*	*length*	*perimeter*	*area*	*Geo-Code*	*name*
point object	√					√	√
linear object			√			√	√
areal object		√		√	√	√	√

2.2.3 MAIN IDEAS

The main idea of probabilistic are based on (Beeri etal., 2004; Tong et al., 2007). Suppose that the map datasets *A* and *B* have *m* and *n* objects, *A* = $\{a_1, a_2, \cdots, a_m\}$,B = $\{b_1, b_2, \cdots, b_n\}$, where *m* may be not equal to *n*. The algorithm selects the multiple measures to calculate the probability of relationship between *A* and *B*. The probability object from *A* to *B* is:

$$P(a_i, b_j)_{(t)} = \frac{delta(a_i, b_j)_{(t)}^{-\alpha}}{\sum_{k-1}^{n} delta(a_i, b_j)_{(k)}^{-\alpha}}$$

$$P(a_i, b_j) = \sum_{t-1}^{r} P(a_i, b_j)_{(t)} \bullet W_t$$

$$\sum_{t-1}^{r} W_t = 1$$

$P(a_i, b_j)_{(t)}$ represents the probability of objects a_i and b_j according to the indicator *t*, and $P(a_i, b_j)$ refers to the holistic probability of objects a_i and b_j. $Delta(a_i, b_j)_{(t)}$ represents the absolute difference of the indicator *t* in a_i a nd b_j. $Delta(a_i, b_j)_{(t)}$ with the value 0 means that a_i and b_j a re matched completely according to the indicator *t*. Parameter *r* is the number of the measure that should be compared. Parameter W_t means the weight of the indicator *t*.

$$P(a_i) = \max(P(a_i, b_1), (P(a_i, b_2), \cdots, P(a_i, b_n))$$

$P(a_i)$ means the maximal probability of with the object a_i in *A*, and with $P(a_i)$ we can obtain the matched objects in *B* to a_i. Parameter *α* is decay factor and here it has the value *2* generally.

Nevertheless, through the probabilistic match, only the most probable one can be determined, which results that there is merely 1-0/0-1 or 1-1 correspondent relationship between the two objects. So in order to identify the exact unambiguous correspondent multiplicity in multi-scale map space, reasonable procedures must be implemented.

2.3 MATCHING PROCESS

In most cases, the matching process starts with an object in the small-scale map and finds the corresponding object, or the combination of objects, in the large-scale dataset that is considered most similar to the current small-scale object. To compare similarity many different measures based on geometrics, semantics and inter-object relationships are used. These measures form an n-dimensional space and the object(s) in the large-scale map that are considered closest to the current small scale object(s) are considered to be the best match. To get the accurate correspondences four steps are prerequisite as follows.

2.3.1 GENERATION OF CANDIDATE MATCHED PAIRS BY BUFFER OVERLAY

The algorithm uses buffer growing (Walter and Fritsch, 1999) and overlap analysis to get candidate objects from one map to another map. Generally, the threshold of buffer is expressed by formula:

$$\text{bufferDistance} = k \cdot \sqrt{m_a{}^2 + m_b{}^2}$$

Parameter *k* in formula is a constant parameter and equal to *3* mostly. Parameter m_a and m_b refer to corresponding preciseness of different scale map *A* and *B*. Distance for point objects, area proportion of the overlay for linear and areal objects are calculated to get the "covered" objects in another map. In figure 2, object *b5∈ B* is carried out a buffer to make overlay analysis, which indicates object *b5* overlay and covers two objects *a7* and *a8∈A* showed in figure 2.

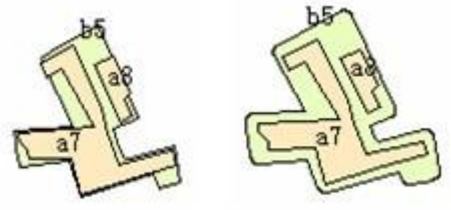


Figure.2 Example of buffer growing and overlay

2.3.2 CALCULATION OF PROBABILITY OF CANDIDATE MATCHED PAIRS

In this step, the algorithm confines the candidate objects that generate in step I with probabilistic match while spatial and non-spatial measures are adapted in probabilistic matching stated in 4.2. The matched results are the corresponding pairs in unidirectional process. In unidirectional match from *B* to *A* the probabilities of *P(b5,a7)* and *P(b5,a8)* are calculated with values *0.945* and *0.832*, respectively. So the object $a7 \in A$ is identified as the corresponding object of object $b5 \in B$ in this unidirectional match.

2.3.3 BIDIRECTIONAL MATCHING

Obviously, unidirectional match can merely identify 1-0 and 1-1 correspondence, which means that $a_i \in A$ may have one corresponding object in B, but the correspondence from *B* to *A* is not clear because the matching is not symmetric. Consequently, the matched correspondences are incomplete, even incorrect in multi-scale map space. Unidirectional matching cannot handle the 1-N or N-1 or N-M relationships, and they may contain false assignments that are inconsistent in map generalization. So bidirectional matching must be implemented to reach the explicit and definite correspondent relationships. Bidirectional match means that the algorithm should carry out the unidirectional match at least twice of two maps with each other. From another unidirectional match of *A* with *B*, we can determine that *b5* is the corresponding object of *a7*, also *b5* is the correspondent to *a8* in the above statement. With mutual analysis, *{a7,a8}* and *{b5}* are the corresponding pairs/sets with each other, which is a correspondence of 1-N or N-1.

2.3.4 JOIN OF THE MATCHED TABLE

We should build a table to record the results of unidirectional probabilistic matching correspondent pairs, so there should be two tables to record the result of bidirectional match. Through the table join, we can find the many-to-one correspondence like *{a7,a8}* to *{b5}*. In the table, candidate count indicates the quantity of candidate matched objects in other map, and matched ID is the correspondent object with the largest likelihood.

Table.3 Unidirectional match from A to B

object ID (A)	*Candidate count*	*MatchedID (B)*	…
10	3	2	
11	1	2	
12	0	0	
13	1	5	
14	1	4	
…	…	…	

Table.4 Unidirectional match from B to A

object ID (B)	*Candidate count*	*MatchedID (A)*	…
1	1	10	
2	2	0	
3	1	10	
4	1	0	
5	1	0	
…	…	…	

For object with ID *10* in map *A*, we can find that it has 3 potential relative objects in map *B* from the first row in table 3 and the most correspondent object is the object with ID *2* in map *B*. In addition, the objects with ID *1* and *3* in *B* are corresponding to the object with ID *10* in *A*, which can be inferred from table 4 with the same principle. So we can draw an inclusion that the corresponding relationship of *{{10},{1,2,3}}* is 1-N correspondence. However, with further analysis, we can find that the object with ID *2* in map *B* has

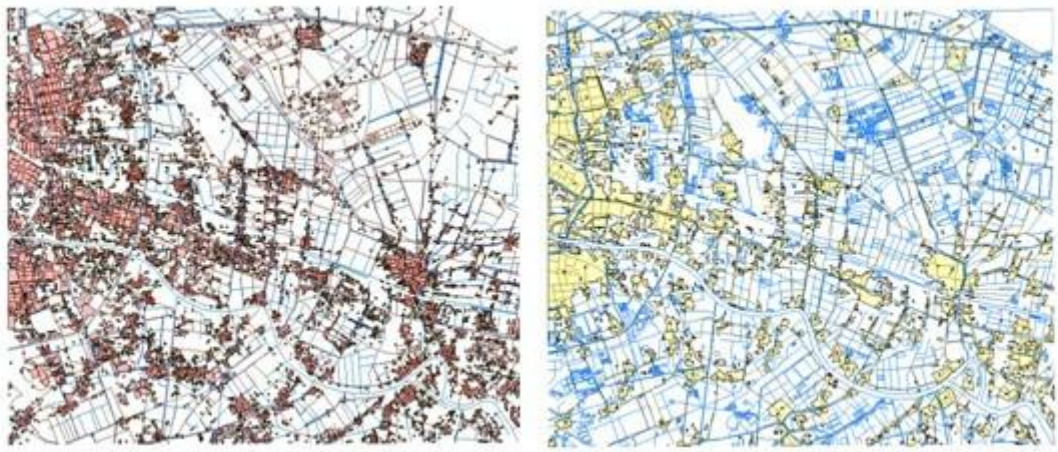
2 potential candidates from the second row in table4, in which the object with ID *10* in *A* is one in the first row in table 3. Another count occurs on the object with ID *11* in *A*, as the second row in table 3 shows. So complete corresponding sets involve five objects between two maps and the mutual multiplex relationship is an M-N correspondence *{{10,11},{1,2,3}}* through the table join. Other corresponding relationships can be considered as the special cases of M-N relationship and can be concluded easily from the table join, like 1-1 corresponding pairs *{{13},{5}}*.

3 RESULTS

3.1 OVERVIEW

Two neighbor-scale maps L(1:10,000) and S(1:50,000) about one region has been tested using the above probabilistic matching algorithm. The features in this area involve liner roads, linear hydrological features, point and areal residences or built-up areas located at east of China. Figure 3 shows the whole scenes of two maps about the same region, and table 5 gives the number of objects in each map.

Map L have better up-to-date data and these two maps have large difference of morphology and number of spatial objects. We can find that the number of geographic objects have the disparity and gap between them. First, it is the information entropy and map legibility that determines the amount of information about geographic objects in different scale maps. Secondly, many generalization operators have many influences on the shape and distribution of map objects as stated in section 2.



L map S map

em>Figure.3 Two neighbor-scale maps about the same test area

Table.5 The number of the objects in two maps

geometry	*feature/class*	*L*	*S*
point	resident	3387	339
line	road	4958	1398
line	hydrology feature	3711	1419
area	built-up areas	5113	1526

For linear object, the division and segment of digitalization may affect a little on the number of objects and matched results. Although, for areal residences and built-up areas, digitalization has very little influence, their shapes and layouts are changed. The extracts for both maps are showed in figure 4. We can find the great difference of the layout of the built-up areas between two maps. The probabilistic match approach of this paper can deal with these complicated many-to-many corresponding relationships between two maps efficiently. The results of bidirectional match of the test area are listed in table 6, and the number of each kind of correspondence and their rate to original number of objects from the viewpoint of large scale map are given in the table.

Figure.4 Extracts of two maps with different layouts in L (left) and S (right)

Table.6 Statistics of corresponding relationships and the rate (from L side, #/L)

	1-0	0-1	M-N	1-M	M-1	1-1
resident point	3158 (93.2%)	110	0	0	0	229 (6.8%)
road line	2452 (49.5%)	949	0	23 (0.5%)	392	423 (8.5%)
hydro-line	2441 (65.8%)	662	0	12 (0.3%)	339	287 (7.7%)
built-up area	1849 (40.0%)	273	128	27 (0.5%)	436	304 (5.9%)

3.2 ANALYSIS OF RESULTS AND DISCUSSION

Although two maps we tested have big temporal span and large difference, certain matching rates are reached from the table 5 and 6. First, there is very small number of objects in larger scale map L that could be divided into several parts in smaller map S, which is determined by the principle of map generalization. Therefore, the number of 1-M correspondence generated by decomposition of four features is very small, 0.5%, 0.3% and 0.5%, respectively. For point and linear objects, there is no M-N correspondence because of their simplicity and dimensionality, as well as 1-M and M- 1 relationship for point objects.

Secondly, the map objects with 1-0 cardinality take high rate in table 6 because of the different up-to-date-states and the constraint of information entropy. From another view, we can state that the objects in 1-0 and 0-1 corresponding relationships are not matched with each other. Noticeably, the high rate of 1-0 correspondence means that there are more new map objects in the large scale map, which is the source data of updating propagation.

More significantly, the situations of multiplicity are apparent different on areal objects. The rate of 1-0 correspondence is lower and the multiple correspondence (M-N,1-M,M-1) of built-up areas is higher than that of point and linear object respectively.

Next, more attention are paid on multiple correspondence and built-up areas are taken as an example. The total count in the row of table 6 is not equal to that of objects in table 5, and the count in table 6 is the number of correspondence, not the number of objects. From table 6 we can find that 304 objects in map L still exist in S, and 27 built-up areas are divided into more objects according to 1-M cardinality. However, for map L, what happened for the left 53.6% objects ((5113-1849-304-27)/5113)? No doubt, they are regrouped and combined into other objects because each M-N or M-1 correspondence may include many objects in map L. So the morphology and layout of area residences are changed between two maps as figure 5 shows. Also the same circumstances happen on other features. Worthily, this high proportion of areal objects in M-N multiplicity has significant applications in map updating and model generalization.

img width="576" height="259" alt="" src="http://resume.europa-organisation.com/_global/files/icc-v2-oral-digital-publication/171/k8uaw8axfzm3amjzqd9s.jpg" />

Figure.5 Different layouts of residences in L (left) and S (right)

Also from the viewpoint of the smaller map, we can make similar matching results. 1-1 and M-N correspondences in table 6 will remain unchanged and other corresponding relationships will be in opposite orders. Also the rate should be calculated based on division by the number of objects in map S. We extend the similar tests in other nine cases that cover urban, suburban and rural regions. And the approach can tell its high ability to identify the corresponding relationships efficiently and effectively.

Many-to-many corresponding relationship breaks the symmetry of 1-1 correspondence, and should attract more attentions. In multi-scale map space, the directions of the matching may have certain meanings, and the corresponding relationships involve different mapping metaphors. In addition, we should consider the difference of scales and their precision, which have affects on the matching results. In other words, the value of spatial similarity degree of the same object or phenomenon in different scale maps is scale-dependent (Yan, 2010).

4 CONCLUSION AND FUTURE PLANS

For actual applications, if the large scale map has fresh and up-to-date data, we can update the objects in the scale-linked map with the corresponding relationships between them to satisfy map model generalization, and the updating can be propagated one by one in the cascade-scale database.

In this paper, we discuss the matching characters in multi-scale map space, and present the probabilistic method to for matching map objects. The approach uses the buffer overlay to generate the candidate corresponding objects, and applies multiple-measure probabilistic match to identify the object with the largest likelihood. Through table join, many-to-many corresponding relationships can be determined. Detail analysis about the matching results are given and discussed with two different maps of one region. The method gains its effects and performance in multi-scale map, which provide a way to update the scale-linked map. In addition, map updating in multi-scale map space based on map matching should be implemented and make further analysis with the rate of data change.

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