OSM/Amap Road Network Matching and Fusion Technology for Road Spatialization: Postprint

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Abstract

The “Six-in-One” road coding constitutes fundamental textual data for locating accidents and violations in traffic management operations, yet lacks spatial location information. Existing commonly utilized road network datasets, such as the Gaode road network, employ multi-lane segment representation and exhibit lower currency relative to OSM road network, rendering them inadequate for traffic management operational requirements. To address these issues, this approach utilizes the Gaode road network as a foundation supplemented by high-currency OSM (OpenStreetMap) road network, applies the LCSS (longest common subsequence) algorithm from trajectory clustering analysis to the road network matching process, and employs the Stroke method for road network fusion on the matched results. Experimental results demonstrate that the LCSS algorithm achieves favorable road network matching performance. Finally, based on this methodology, a road network matching and fusion software system was developed and deployed at the Wuhan Traffic Management Bureau.

Full Text

Application of OSM/Gaode Road Network Matching and Fusion Technology in Road Spatialization

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Abstract

The “Six-in-one” road code serves as fundamental textual data for locating accidents and violations in traffic management operations, yet it lacks spatial location information. Existing commonly-used road network data, such as Gaode (Amap) road networks, represent roads through multi-lane segments and exhibit lower currency compared to OSM (OpenStreetMap) road networks, making them inadequate for traffic management business requirements. To address these issues, this paper employs Gaode road network as the foundation and supplements it with high-currency OSM road network, applying the LCSS (Longest Common Subsequence) algorithm—commonly used in trajectory clustering analysis—to the road network matching process, and subsequently utilizing the Stroke method for network fusion after matching. Experimental results demonstrate that the LCSS algorithm achieves favorable road network matching performance. Finally, a road network matching and fusion program was developed based on this approach and has been deployed at the Wuhan Traffic Management Bureau.

Keywords: road network matching; LCSS algorithm; road network fusion

0 Introduction

Spatial target matching encompasses point feature matching, linear feature matching, and polygon feature matching, with road network matching belonging to the category of linear feature matching. The Wuhan Traffic Management Bureau currently relies primarily on the "Six-in-one" road code for accident and violation localization. This code constitutes textual data that lacks spatial information, making it difficult to satisfy the informatization and refinement demands of traffic management operations. Meanwhile, the existing road network data available to the bureau originates mainly from Gaode's multi-lane road network data, which suffers from untimely updates. Moreover, for accident and violation localization in traffic management operations, Gaode's overly refined multi-lane road network fails to meet practical application requirements. Consequently, integrating high-currency OSM road network data presents a viable solution for road network matching and spatialization of the "Six-in-one" road code.

Research and applications in road network matching have remained one of the most active directions in the GIS field. Current linear feature matching methods primarily fall into five categories: (a) geometric matching, which calculates geometric similarity between two spatial entities; (b) topological matching, which uses topological relationships of homonymous entities as matching criteria; (c) semantic matching, which calculates similarity of entity names; (d) probability-based matching algorithms, which determine matching entities by calculating matching probabilities; and (e) intelligent algorithms such as ant colony algorithms and hidden Markov models to seek globally optimal road network matching solutions. Additionally, many scholars have improved matching accuracy by incorporating constraints or combining multiple algorithms. Domestic researcher Liu Yining [1] conducted homologous road network matching across different temporal phases in a Shanghai region using a buffer growth algorithm. Guo Qingsheng et al. [2] selected road network data from Nanchang with minimal scale variation and Hefei with significant scale variation, proposing a road network matching algorithm that considers scale change and data updates. Zhang Yunfei et al. [3] utilized probabilistic relaxation for multi-source road network matching in Wuhan and Zurich, Switzerland. Gong Xianyong et al. [4] demonstrated that ant colony algorithms effectively seek globally optimal matching solutions for road network homonymous entities. However, most road matching research focuses on homologous road network matching or multi-scale [5,6] road network matching across different scales.

This paper addresses Wuhan traffic management business requirements by using Gaode road network data as the foundation and supplementing it with current OSM (OpenStreetMap) road network data to fill partial data gaps in Gaode road network, achieving heterogeneous road network matching. The LCSS (Longest Common Subsequence) algorithm [7], commonly used in trajectory clustering, is employed to match Gaode and OSM road networks. Finally, a road network matching and fusion program was developed based on this approach.

1 Road Network Data Analysis

This study utilizes two primary spatial datasets: Gaode road network data and OSM road network data.

1.1 Gaode Road Network Data

Gaode road network relies on advanced data collection methods, proprietary electronic map production processes, and geographic data editing and verification systems to form extensive and accurate geographic information. Its data quality is high, with the vast majority being self-collected data. Gaode road network data is relatively complete, with more refined production processes and higher geometric precision, offering unparalleled advantages over other road network data sources. Its coordinate system employs an encrypted system called the Mars Coordinate System, which exhibits non-linear deviation from WGS84 coordinates. The Gaode road network data used in this paper encompasses over 160,000 road segment records in Wuhan, including the important field information shown in .

Before matching Gaode road network data with OSM road network data, four major challenges arise from Gaode' s refined representation:

a) A complete road in Gaode network is divided into multiple segments, requiring spatial connectivity analysis to determine whether they belong to the same road.

b) Gaode network data contains multi-lane information, yet traffic management accident and violation localization does not distinguish between bidirectional multi-lane issues. Therefore, this paper simplifies the road network by merging multi-lanes and simplifying complex linear roads during processing.

c) Road network information is missing. Although Gaode network is complete, nearly half of the network lacks road names.

d) Over 10,000 segments have aliases. These segments have their own names, but their aliases may represent broader conceptual roads, such as national/provincial/county/township roads, second/third ring roads, and beltways.

1.2 OSM Road Network Data

Over the past decade, platforms based on user-generated geographic data have gradually emerged, with various types of geographic data (maps, satellite imagery, road network data, GPS terminals) collected and shared by users on platforms like OpenStreetMap (OSM) [8,9]. Since its launch in 2004, OSM has accumulated 2 million users. Due to its simple operation without requiring complex GIS skills, geographic information enthusiasts worldwide can promptly upload and update road information they are familiar with. OSM data offers advantages including rapid update speed, high currency, and low acquisition cost. These merits have attracted extensive research from domestic and international GIS scholars on VGI data quality, reliability, and applications. For instance, Zielstra et al. [10] compared OSM and TeleAtlas data in Germany, finding that although OSM data coverage in suburban areas was limited, it was abundant in larger cities (e.g., Berlin, Frankfurt, Munich) and could serve as an alternative data source for many projects. Luo Luchang et al. [8] demonstrated that domestic OSM data' s road length and name attribute completeness is comparable to Baidu Maps and Google Maps. Wang et al. [11] studied OSM data quality in Wuhan from three aspects: data completeness, attribute accuracy, and positional accuracy, concluding that OSM data can serve as a new data source for high-grade urban transportation networks and suburban road networks.

Wuhan' s OSM road network contains 19,000 records, primarily including the field information shown in .

2 Road Network Data Preprocessing

This paper uses Gaode road network data as the foundation and requires preprocessing before road network matching. Gaode network, as multi-lane road network data, presents complexity in linear patterns as the primary challenge for subsequent processing, whereas OSM network, as single-lane road network data, requires no preprocessing. After analyzing Gaode network' s spatial characteristics, this paper considers five aspects for simplification: eliminating small fragments between multi-lanes, eliminating highway ramps, merging multi-lanes, eliminating fragments near main roads, and simplifying complex linear roads.

2.1 Eliminating Small Fragments Between Multi-lanes

In Gaode road network data, small fragments like those shown in [Figure 1: see original paper] contribute little to traffic management operations such as accident localization, only increasing road network structural complexity and substantially raising data preprocessing difficulty while creating significant interference during multi-lane merging and ramp elimination.

This paper therefore conducts corresponding simplification processing based on fragment characteristics. By analyzing existing Wuhan Gaode road network data, the main characteristics of small fragments include short length, adjacent or intersecting homonymous road segments, and large angles formed with small fragments. Accordingly, this paper sets a length threshold and an angle threshold , then follows this processing workflow:

a) Filter segments with length less than the threshold (selecting appropriate l values).

b) For qualified segments from step a), conduct intersecting spatial queries iteratively to identify how many segments intersect each segment. If the number of intersecting homonymous segments is greater than or equal to 2, and all intersect at angles greater than threshold , the segment is identified as a fragment and removed.

Note that parameters mentioned herein refer to empirical values unless otherwise specified, with specific values determined according to different datasets.

2.2 Eliminating Highway Ramps

As shown in [Figure 2: see original paper], highway ramps create extremely complex spatial relationships in the road network. Ramps, as highway accessories with complex shapes, are particularly unfriendly for data preprocessing. Given that this research focuses on traffic violation and accident localization, hierarchical relationships and refined road expressions are not applicable, necessitating highway simplification.

This paper identifies three characteristics of ramps: (a) short length; (b) high curvature, presenting arc shapes; and (c) generally intersecting with two roads. By setting a length threshold, an average segment turning angle threshold, and a ramp sub-segment threshold, segments shorter than the length threshold are selected. For candidate segments, spatial analysis is performed to select connected segments. If the number of non-homonymous connected segments is greater than or equal to 2, the average turning angle exceeds the threshold, and the number of ramp sub-segments exceeds the sub-segment threshold, the small fragment is determined to be a highway ramp. Data processing effectiveness depends on the selection of length and angle thresholds; ramps that cannot be eliminated automatically are processed manually.

2.3 Multi-lane Merging

This process involves the largest data volume in preprocessing. This paper first calculates segment slope k, then at the quarter point, center point, and three-quarter point of the segment, constructs segments with slope -1/k and length . Spatial intersection queries are performed—if all three points have intersecting segments with identical road names and similar directions to the selected segment, they are determined to be redundant lanes, and the centerline calculated from multiple lanes becomes the final simplified road.

After multi-lane merging, road network structure achieves certain simplification and optimization, yet some cases remain unprocessed: (a) when segment length is short and multi-lane correspondence is not neatly aligned, detection probability decreases significantly; (b) certain misjudgments occur, such as when two roads are very close but not actually multi-lane roads, commonly found in residential alleys. To improve processing effectiveness, prior knowledge is incorporated: for case (a), the characteristic that adjacent homonymous roads have small direction turning angles is used as an identifier to determine segment properties; for case (b), surrounding network characteristics are analyzed (if it' s an alley, it exhibits a grid-like pattern spatially) to determine whether they represent one road or two closely spaced roads.

2.4 Eliminating Fragments Near Main Roads

The road network contains many fragments connected to main roads or extending from main road branches. These fragments affect network complexity, and deleting these unimportant fragments has minimal impact on network integrity and structure.

2.5 Simplification of Complex Linear Roads

Some roads exhibit complex linear patterns, typically combining multiple forms such as multi-lane highways with ramps and fragments. Such cases require comprehensive processing combining the aforementioned scenarios.

3 Road Network Matching and Fusion

3.1 Road Network Matching

Nearly half of Gaode road network segments lack road names. Without utilization, this causes considerable waste of spatial data, as missing roads may have supplementary information in other networks. OSM, as an open-source mapping community gathering worldwide mapping enthusiasts with long data accumulation history, high update frequency, and broad coverage, serves as a reliable map data source. This paper uses OSM road network data to supplement Gaode road network data, filling gaps in road name information. Since the matching data sources are Gaode map data and OSM road network data, with the former lacking road names, matching can only rely on geometric characteristics of spatial data. Linear feature geometric characteristics primarily include position, direction, length, and turning angle (total angle turned by the linear feature), plus topological characteristics—positional relationships with adjacent features. The matching method employed herein utilizes position, length, and direction information. Topological relationships are not used as matching conditions due to the large data volume from both sources and the need to build topological relationships, which would entail excessive computational cost unsuitable for practical production.

Additionally, both datasets contain numerous records: OSM road data features better road integrity with fewer fragments (19,000 records), while Gaode network has over 160,000 records. To accelerate matching processing, this paper uses R-tree indexing for the OSM network (the network to be matched). The road network matching workflow is shown in [Figure 3: see original paper].

During road matching, this paper adopts the LCSS algorithm for road matching, detailed in Section 3.1.2.

3.1.1 Overview of Road Network Matching Methods Road network matching constitutes a crucial component of multi-source map spatial data matching and fusion. Based on current domestic and international research, geometric characteristic-based road network matching methods fall into two categories:

a) Buffer growth method [12,13]. This algorithm first uses candidate segments' buffers to determine candidate arc sets, then directly performs matching judgment on candidate arcs. As shown in [Figure 4: see original paper], appropriate Buffer-v and Buffer-p values benefit matching results, typically adapting these values automatically based on matching conditions. Initial Buffer-v and Buffer-p values are empirically determined.

b) Iterative Closest Point (ICP) method [14]. This approach first performs initial matching on nodes where road network arcs intersect; based on node matching results, it continues matching judgment on arcs associated with matched nodes. The process iterates until all road arc matching is complete.

Both methods require consideration of geometric features in road networks, including distance, shape, and angle. Road arc distance calculation differs from Euclidean distance between two points and is more complex. Common linear feature distance measures fall into two categories:

a) Warping-based distance. Euclidean distance, Manhattan distance, or other L-p norm distances are most common. Several warping-based distance methods include Dynamic Time Warping (DTW) [15] and subsequent Longest Common Subsequence (LCSS) [7], Edit Distance on Real Sequence (EDR). These methods share the same definition but employ different cost functions.

b) Shape-based distance. 主要包括 Hausdorff distance and Fréchet distance. Traditional Hausdorff distance is computationally straightforward but has poor noise resistance. To address noise pollution and occlusion issues, Huttenlocher (1993) proposed the partial Hausdorff distance concept [16]. Another metric is Fréchet distance, proposed by French mathematician

Maurice René Fréchet in 1906 to describe path space similarity, approximating curve Fréchet distance using polyline vertex information, though its computation is relatively complex.

3.1.2 LCSS Algorithm Given that LCSS algorithm is commonly used in trajectory clustering analysis but rarely applied in road network matching, this paper attempts its application in road network matching. The LCSS algorithm offers three advantages:

a) Not all elements require matching. Euclidean distance and DTW methods must match all elements, including outliers. When matching OSM and Gaode networks, the sampling rates differ (OSM network annotated by internet users has lower sampling rate; Gaode network collected by professional map vendors has higher sampling rate), and OSM network maintains better road integrity while Gaode network segments roads into multiple segments. DTW requires truncation when processing data of different lengths, which can reduce matching quality, whereas LCSS requires no truncation.

b) Existing research shows LCSS model computation is more efficient than Euclidean distance and DTW [7].

c) Euclidean distance and DTW have poor noise resistance. Since LCSS doesn' t require considering all data, it exhibits better noise resistance.

LCSS (Longest Common Subsequence) [7,17,18] refers to the longest common subsequence present in two or more sequences. Its main idea employs dynamic programming to calculate the longest common subsequence between sequences. In road networks, due to differences in multi-source data, two roads cannot completely coincide, so the condition for determining common points is whether the horizontal and vertical coordinate differences between two points are within threshold range. If within threshold, they are considered the same point and LCSS length increases by 1.

Several definitions are provided. Assume all points are two-dimensional points. Let A and B be two roads with n and m points respectively, where A = ((x_1 , y_1), ···, (x , y)) and B = ((x_1 , y_1), ···, (x , y)).

Definition 1 LCSS is defined as follows: LCSS(i,j) represents the number of points in the common subsequence between the subsequence composed of the first i points in A and the subsequence composed of the first j points in B.

Definition 2 Given threshold , function close determines whether two points are the same point:

close(a,b) = true if |x - x | < and |y - y | < , otherwise false.

Definition 3 Function S represents similarity between two roads: S(A,B) = LCSS(A,B) / min(n,m). The threshold for S(A,B) is 0.6; similarity exceeding 0.6 indicates basic matching between two roads. If multiple matching segments exist, the segment with highest matching degree is selected as the hit segment. Actual processing effectiveness depends on preprocessing quality, network characteristics, and threshold values. Note that indexing must be established before road network matching.

3.1.3 Algorithm Implementation The LCSS algorithm pseudocode is as follows:

Algorithm: LCSS Algorithm

Input: Two coordinate strings to be matched.

Output: DP matrix for LCSS.

```
Function getTypeMatrix(coors1, coors2):
    m $\leftarrow$ coors1.length
    n $\leftarrow$ coors2.length
    type $\leftarrow$ new int[m][n]
    for i $\leftarrow$ m to 1:
        for j $\leftarrow$ n to 2:
            if isClose(coors1[i], coors2[j]):
                type[i,j] $\leftarrow$ type[i+1,j+1] + 1
            else:
                type[i,j] $\leftarrow$ Math.max(type[i][j+1], type[i+1][j])
    return type

Function isClose(point1, point2):
    x_{abs} $\leftarrow$ |point1.x - point2.x|
    y_{abs} $\leftarrow$ |point1.y - point2.y|
    if x_{abs} < distThre && y_{abs} < distThre:
        return true
    return false

Function getMatchRatio():
    ratio $\leftarrow$ this.LCS.length / Math.min(L1.length, L2.length)
    return ratio
```

The LCSS algorithm relies on the following data structures: Coordinate[] L1 (coordinate string 1), Coordinate[] L2 (coordinate string 2), Coordinate[] LCS (matched common coordinate string), double distThre (distance threshold for coordinate differences), double matchRatio (matching degree), int commonLen (common coordinate string length), and static final double DEFAULT_{DISTTHRE} = 0.0005 (coordinate difference threshold of approximately 0.001, corresponding to 80-90m on map). The Coordinate class contains longitude and latitude member variables.

3.2 Road Network Fusion

Current urban road networks often divide road elements into multiple segments, destroying road integrity. Gaode road network similarly segments many roads, where a semantically complete and spatially continuous road may be split into multiple segments. Therefore, road network fusion in this paper primarily refers to concatenating such segmented roads into smooth, seamless complete roads.

The Stroke method is an important segment concatenation approach in road generalization, adopted herein for its simplicity and effectiveness. However, traditional Stroke methods randomly select starting segments, producing different Stroke concatenation results in repeated experiments. Therefore, this paper considers road class as road importance to define processing order during segment concatenation, ensuring fixed Stroke connection results. During network fusion, a Stroke connection method considering road semantic names and road classes is used, employing the self-best-fit (SBF) strategy [19]. SBF selects the most suitable segment as the concatenation segment based on requirements; this paper uses geometric rules for determination, specifically maximizing the angle between concatenated segments.

The algorithm' s main steps are:

a) Sort road network by road importance level, using the sorting result as Stroke connection processing order.
b) Perform network concatenation in order. First check if road name is empty, processing named and unnamed segments according to steps c) and d) respectively.
c) For named segments, directly concatenate if a homonymous segment exists nearby; otherwise, do not concatenate.
d) For unnamed segments, concatenate according to "road class—minimum angle" priority order. This means if an unnamed segment of the same class exists nearby and their angle exceeds a certain threshold, they are determined to be the same road; otherwise, they are not concatenated.

Segments not satisfying any processing rules remain unprocessed. During processing, once a segment has been concatenated, it is marked to exclude it from future Stroke concatenation considerations.

Two main scenarios require consideration during network fusion: non-intersection road Stroke connection (Figure 5: see original paper) and intersection Stroke connection (Figure 5: see original paper).

3.2.1 Non-Intersection Road Stroke Connection For non-intersection road Stroke connection, processing order is first defined according to road importance level, i.e., using Gaode network's ROAD_{CLASS} field. While Figure 5: see original paper only shows four segments A, B, C, D where SBF works without issues, SBF randomly selects starting segments when processing many segments, yielding non-fixed Stroke results. Therefore, this paper improves SBF by using road class as processing order, avoiding this problem.

3.2.2 Intersection Stroke Connection For intersection Stroke connection, a crucial prerequisite is intersection feature identification. For intersections like Figure 5: see original paper, the presence of ring segments is determined by whether the total turning angle of segments approximates 360° (not exactly equal due to potential incomplete connections). After feature identification, processing similar to Section 3.2.1 concatenates segments interrupted by intersections.

4 Experiments and Application

4.1 Road Network Matching and Fusion Experiment

To verify the application effect of matching and fusion technology in road spatialization, this paper 截取 d partial Wuhan area data for comparison. The original Gaode road network data is shown in [Figure 6: see original paper]. The preprocessed and matched/fused network is shown in [Figure 7: see original paper], demonstrating that multi-lane merging, fragment elimination, and other simplifications produce a cleaner network.

Network matching results are shown in [Figure 9: see original paper], where solid lines represent OSM network and dashed lines represent simplified Gaode network, indicating good matching performance.

Preprocessing effects can be observed in [Figure 8: see original paper]: (a) and (f) show highway ramp elimination; (b) and (g) show multi-lane merging; (c) and (h) show elimination of fragments between multi-lanes; (d) and (i) show elimination of fragments near main roads; (e) and (j) show simplification of complex roads.

4.2 System Application

Under Wuhan' s road spatialization requirements, this paper developed a road network matching and fusion program that has been successfully applied at the Wuhan Traffic Management Bureau. The program employs .NET COM components, GDAL spatial library, and ArcObject toolkits to provide coordinate system conversion, road data preprocessing, attribute calculation, road simplification, and network fusion services.

The prototype system interface is shown in [Figure 10: see original paper]. The left panel provides layer management with data addition, zoom, pan, and save functions; the middle section displays data; the upper right section provides parameter settings; and the lower right section shows the entire network processing workflow. Users can customize parameter values based on actual processing effects, with parameters including curvature range, road angle, and buffer distance. One-click network processing simplifies system operation.

Additionally, the system' s network matching and fusion functions have been applied in other systems, as shown in [Figure 11: see original paper].

5 Conclusion

Currently, the Wuhan Traffic Management Bureau uses text descriptions for accident and violation localization. With the popularization of mobile PDAs and road management updates and maintenance, the necessity of spatial road network data becomes increasingly prominent. This paper designed and developed a multi-source road network matching and fusion system that addresses complex multi-source network management, maintenance difficulties, and time-consuming manual operations. The system has been deployed at the Wuhan Traffic Management Bureau, providing road network data support for accident and violation localization and making important contributions to Wuhan traffic management informatization and road spatialization.

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Note: Figure translations are in progress. See original paper for figures.