

## ROAD NETWORK EXTRACTION USING GPS TRAJECTORIES BASED ON MORPHOLOGICAL AND SKELETONIZATION ALGORITHMS

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### ABSTRACT:

In this article, a method for road network extraction is proposed, based on GPS (Global Positioning System) trajectories. Unlike existing methods, it is not necessary to resample the GPS trajectories into a raster structure; instead, all analyses are based on the polylines that represent the GPS trajectories. Basically, a morphological analysis and a skeletonization technique are used by the proposed method. Two main steps of the method can be identified: the first step consists in generating an elongated polygon (that delimitates an elongated ribbon) that represents the selected road; and the second step aims at reconstructing the road network. The proposed method was evaluated based on four GPS trajectory datasets and the results obtained can be considered good, but some inconsistencies were noted, as for example: extraction failures occur in places with very low trajectory density (such as 3-4 trajectories); merging of very close and parallel roads; some road crossings that are close to one another have been merged into a single point. The proposed method was also compared with existing methods in the literature and the obtained results showed good consistency between them.

### 1. INTRODUCTION

The extraction or updating of the road network, if performed manually, may become outdate even before its completion, mainly due to the time required for each updating. Consequently, the development of automatic or semi-automatic methods that speed up the extraction of the road network from optical and/or non-optical data, commonly treated as road extraction methods, has been receiving attention of researchers for several decades. Recently, the trajectory of the road network was performed using GNSS (Global Navigation Satellite System) data.

The use of digital images for extracting the road network began with the pioneering work of Bajcsy and Tavakoli (1976) and, since then, many methods have been developed to explore different aspects of radiometric, geometric, topological, functional, and contextual characteristics of roads. These methods can be classified according to different criteria, as e.g. the degree of automation involved, which can be automatic (Dal Poz et al., 2010; Maboudi et al., 2016; Panboonyuen et al., 2017) or semi-automatic (Dal Poz and Silva, 2003; Dal Poz et al., 2012; Miao et al., 2013; Martins et al., 2015).

The acquisition of GNSS trajectories via automotive navigation systems or smartphones has been used in the prediction of urban traffic conditions and in the extraction of the road network (Goodchild, 2007; Zhang et al., 2010; Cao and Sun, 2014). Several projects have been designed to take advantage of this data, such as the well-known OpenStreetMap project (Haklay and Weber, 2008). The basic objective of this project is to create editable and free-to-use road maps. The main challenge for processing GNSS trajectories is the low quality of individual trajectories. Consequently, the separation of adjacent roads and, mainly, lanes of the same road, is not a simple task (Sayda, 2005).

The basic problem of road extraction in the present context is the reconstruction of road centerlines and/or the identification of road lanes using dense GNSS trajectories. The most commonly used principle for determining the road centerline is based on histograms constructed along road cross sections. These histograms should tend to be normally distributed as the number of GNSS trajectories becomes quite large (Chen and Krumm, 2010). The sample mean for each histogram corresponds to the best local position of the road centerline. Schroedl et al. (2004) proposed a method based on the k-means grouping to separate the road lanes. Basically, groupings are determined along the GNSS trajectories at predefined distances, generating centroids that define the centerlines of the road lanes. Davies et al. (2006) used the Voronoi Diagram to extract the road centerlines from a density map of trajectory points. Chen and Krumm (2010) used a Gaussian mixture model to model the distribution of GNSS trajectories across multiple road lanes. This approach requires some a priori information, like the lane width and corresponding uncertainties. Guo (2008) also used a grouping method, but introduced the strategy of using the vehicle speed, available along the GNSS trajectories, to help in the identification of road exits. Chen and Cheng (2008) developed a method for extracting road centerlines by using morphological operations. Biagioni and Eriksson (2012) proposed a method to correct the geometry and topology of the inferred road map, mainly by mitigating GPS (Global Positioning System) errors. Yuan and Cheriadat (2016) combined aerial images and GPS trajectories for extracting the road centerlines by using an image segmentation framework that is based on the GPS trajectories' location. In Ezzat et al. (2017), first the Douglas-Peucker algorithm is applied to GPS trajectories; then, the simplified trajectories are used to extract the road centerlines by using a grouping technique. Yang et al. (2018) proposed a Delaunay

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triangulation-based method for extracting roads from GPS trajectories. In Munoz-Organero et al. (2018) a machine learning approach is used to automatically detect the road network elements (like traffic light, road crossing, roundabout etc.) using velocity and acceleration patterns associated to GPS trajectories. Li et al. (2019) combined GPS trajectories with Remote Sensing images for producing road map using a deep convolutional neural network model. The hidden Markov chain model was used by Francia et al. (2019) for extracting and updating road map using GPS trajectories.

In this article, a method for road network extraction is proposed, based on GPS trajectories. Unlike existing methods, it is not necessary to resample the GPS trajectories into a raster structure; instead, all analysis operations are based on the polylines that represent the GPS trajectories. Basically, a morphological analysis and a skeletonization technique are used by the proposed method. This paper is organized as follow. Section 2 presents the proposed method. Experimental results and related discussions are presented in Section 3. Finally, Section 4 summarizes the main conclusions.

## 2. PROPOSED METHOD

The input data is a set of polylines that represent GPS trajectories for a road. The method is based on two main steps: the first step consists in generating an elongated polygon (or ribbon) that represents a selected road; and the second step aims at extracting the road centerline. The first step comprises several mathematical operations to build an elongated ribbon for each road, with a width approximately equal to the width of this road. The main mathematical operations are: transformation of each GPS trajectory (that is, a polyline) into an elongated polygon, resembling the morphological dilation operation; merging of the polygons, generating a first representation of the road in the form of an elongated ribbon; filling holes or gaps in the ribbon; removal of branches connected to the road ribbon; geometric regularization of the road ribbon. The second step aims at reconstructing the road network. First, a skeletonization strategy via Voronoi diagram is employed to extract the centerlines of the previously generated ribbons, also allowing the extraction of the road crossing points. Then, inconsistencies on extracted road crossings are removed. The two main steps of the method are described below in subsections 2.2 and 2.3. Before, however, a brief description of the input data of the proposed method, that is, the GPS trajectories, is presented in Subsection 2.1.

### 2.1. GPS Trajectories

Crowdsourcing is an alternative to traditional mapping methods, which normally require equipment, methods, and specialized personnel. Currently, the user himself was included in the mapping process, via data provision, voluntarily or not. In crowdsourcing context, the World Wide Web has a fundamental role, being generically called Web 2.0 (O'Reilly, 2007).

Crowdsourcing can be defined as a type of shared online activity in which an individual, an institution, a non-profit organization or a company proposes to a group of individuals of varying knowledge, composition and quantity, through an open and flexible call, the voluntary commitment of a task (Arolas and Guevara, 2012). Numerous devices are used to disseminate data over Web 2.0, such as: personal computers; smartphones, wristwatches, automotive navigator; vehicle monitoring system, network of surveillance cameras etc..

The collection of geographic locations using portable equipment is largely carried out using GNSS solutions. The GNSS encompasses several global satellite navigation systems, such as: the GPS (USA); GLONASS (Russia); Galileo (Europe); and Beidou (China). These systems were designed to determine the position and speed of the receiver over time. In the context of crowdsourcing, GPS is widely used in the massive collection of vehicle trajectories. Usually, the positioning technique used is the simplest among the existing ones for GPS positioning, i.e., the simple point positioning (SPP), which has accuracy of the order of 6-10 m (Haklay and Weber, 2008). The SPP is based on the ephemeris transmitted and on at least 4 pseudodistances.

A GPS trajectory ( $T_j$ ) is composed of a sequence of spatiotemporal information, which can be expressed as:  $T_j = [I_1; \dots; I_n]$ . Each component  $I_i$  has the following structure:  $(P_i; t_i; A_i)$ , where:

- $t_i$  is the sampling GPS time of the component  $I_i$ ;
- $P_i$  is the position of the vehicle at a time  $t_i$ , defined by the geodetic coordinates  $\phi_i$  - latitude,  $\lambda_i$  - longitude, and  $h_i$  - geometric altitude;
- $A_i$  is a set of attributes, such as speed ( $V_i$ ) and the GPS observable ( $O_i$ ) (if available, it can be used by the user to improve the position  $P_i$ ).

A road ( $R_k$ ) is a collection of trajectories, that is:  $R_k = \{T_1; \dots; T_m\}$ , where  $m$  is usually large. In order to enable the storage and dissemination of GPS trajectories in collaborative mapping projects, it is necessary to use an appropriate data format. The GPX format (GPS eXchange Format) (<https://www.topografix.com/gpx.asp>), mainly due to its high compatibility with various devices and services, has been widely used. General information is stored in the header of a GPX file, such as: the version of the GPX standard used; the identification of the application or device that created the file etc.. Each record is based on the GPS standard, with coordinates in the WGS-84 system: latitude and longitude in decimal degrees; altitude in meters; and date/time in Universal Time Coordinated (UTC).

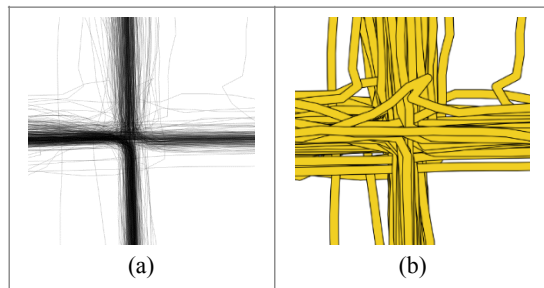
### 2.2. Road Representation by a Ribbon Model

The proposed method is based on positional information only; thus, a given road  $R_k$  is represented as  $R_k = \{T_1; \dots; T_m\}$ , where  $T_j = [I_1; \dots; I_n]$  and, as  $I_i$  can be placed as dependent only on positional information ( $P_i$ ), one can simplify the notation of  $T_j$  as  $T_j = [P_1; \dots; P_n]$ . As points  $P_i$  are originally defined in geodetic coordinates  $(\phi_i, \lambda_i)$ , a transformation of coordinates into a Cartesian coordinate system is necessary to enable the application of the proposed processing to represent each road by a ribbon. The UTM (Universal Transverse Mercator) coordinate system is adopted to represent each point  $P_i$  as  $(E_i, N_i)$ . In general, trajectories are expected to concentrate around the most likely trajectory (the goal of our extraction method, i.e. the road centerline). Although this is statistically expected, later on a strategy is presented to eliminate isolated trajectories.

For each trajectory  $T_j$  (i.e. a polyline), collected along the roads, a buffer with semi-width  $w$  is generated, which is defined by two symmetrical lines around the trajectory  $T_j$  and closed at their endpoints. It is therefore an elongated polygon, or an elongated ribbon, with a width of  $2w$ . This operation is called  $\text{buffer}^+$ , which is similar to the morphological process of dilation.

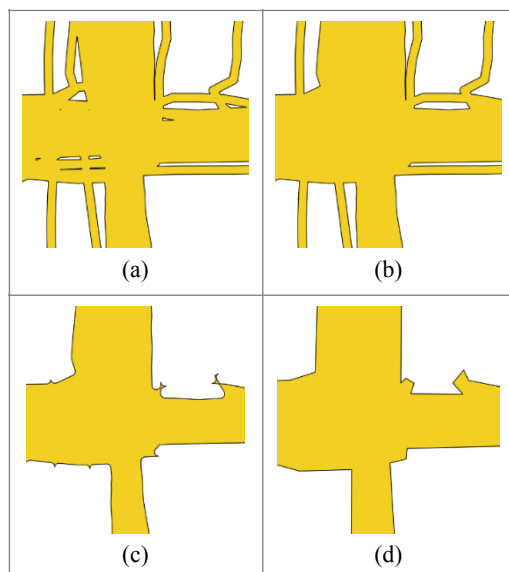
Since the redundancy of GPS trajectories is usually high, the GPS trajectories are close to one another (Figure 1a). As a result, ribbons generate by the  $\text{buffer}^+$  operation will present a desired overlap (Figure 1b). It is recommended to consider the redundancy of available GPS trajectories to define the

buffer width, as few trajectories will require a larger width for the buffer, while a large redundancy will allow for a smaller width.



**Figure 1.** (a) GPS trajectories; (b) buffer<sup>+</sup> operation.

The next step consists in merging the generated ribbons, removing superposed areas (Figure 2a). However, due to possible gaps between the ribbons generated by the buffer<sup>+</sup> operations, it is possible to remain few small gaps inside the road ribbons, as e. g. ones shown in Figure 2a. As these gaps usually have small areas, they are easily eliminated by the minimum area criterion (Figure 2b). Also, due to the low accuracy of the SPP positioning method, isolated trajectories can be generated. Consequently, the buffer<sup>+</sup> operation can also generate isolated and elongated ribbons for these trajectories. These undesired ribbons are usually connected to the main trunk of the road (Figure 2b); moreover, their widths are equal to the buffer width used in the buffer<sup>+</sup> operation. In order to mitigate this problem, an operation called buffer<sup>-</sup> should be applied (Figure 2c). The buffer<sup>-</sup> operation can be interpreted as an inverse operation of buffer<sup>+</sup> operation. In this case, the semi-width ( $w'$ ) is adopted as negative, in which  $|w'|$  ( $|\cdot|$  is the absolute value operator) is slightly larger than  $w$  (the semi-width parameter of the buffer<sup>+</sup> operation).



**Figure 2.** (a) Merging the generated ribbons; (b) buffer<sup>+</sup> operation; (c) buffer<sup>-</sup> operation; (d) simplifying the road ribbon.

The buffer<sup>-</sup> operation not only eliminates the noisy ribbons, but also reduces the width of ribbons that represent roads. In

other words, the buffer<sup>-</sup> operation is similar to the erosion morphological operation.

The buffer<sup>-</sup> operation is algorithmically implemented according to the following principle: noting that noisy ribbons are delimited by parallel lines, ribbons delimited by lines that are far by an amount of  $w'$ , are eliminated; otherwise, ribbons' boundary lines are moved inward.

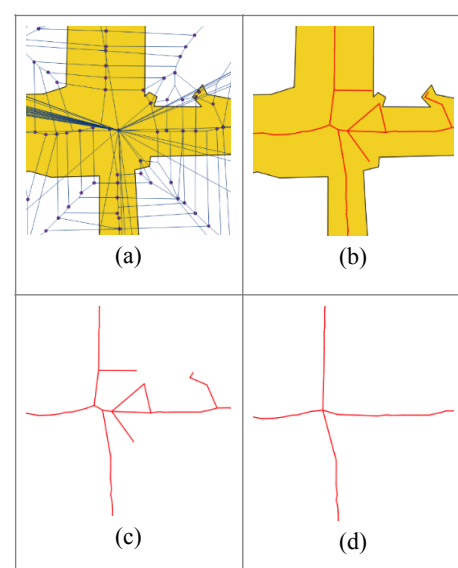
The buffer<sup>-</sup> operation can produce irregularities along the road ribbon boundary lines (i.e., polylines). One way to minimize these irregularities is by simplifying the road ribbon boundary polylines, removing vertices that describe details in excess (Figure 2d). This simplification is carried out in two sequential steps:

- Initial simplification using the Douglas-Peucker polygonization algorithm (Visvalingam and Whyatt, 1990): this algorithm replaces the original polyline with a simplified one with fewer vertices. The simplified polyline is recursively generated, such that their vertices are at the maximum allowed distance from the original polyline.
- Another dilation (i.e., a buffer<sup>+</sup> operation) and Douglas-Peucker simplification applied to the simplified polyline: these operations are carried out with the same parameters previously defined, allowing the reconstruction of the road ribbons with geometric characteristics (smoothness and width) closer to the segment of the represented road.

Another benefit of both post-processing steps is the generation of much more compact representations.

### 2.3 Road Network Reconstruction

The road centerlines, along with initial road crossing points, are extracted by skeletonizing the road ribbons. The skeletonization process used in this work is based on the Voronoi diagram. Given a discrete set of points, usually referred to generating points, the Voronoi diagram of these points is the partition of the corresponding space into cells that follow the two basic properties: each cell contains only one generating point ( $p$ ); and, in addition, all locations inside this same cell are nearer to generating point  $p$  than to other generating points (Ogniewicz and Ilg, 1992).



**Figure 3.** (a) Voronoi diagram; (b) center line obtained from the diagram; (c) segments to be removed by geometric filtering; (d) axis of the extracted road network

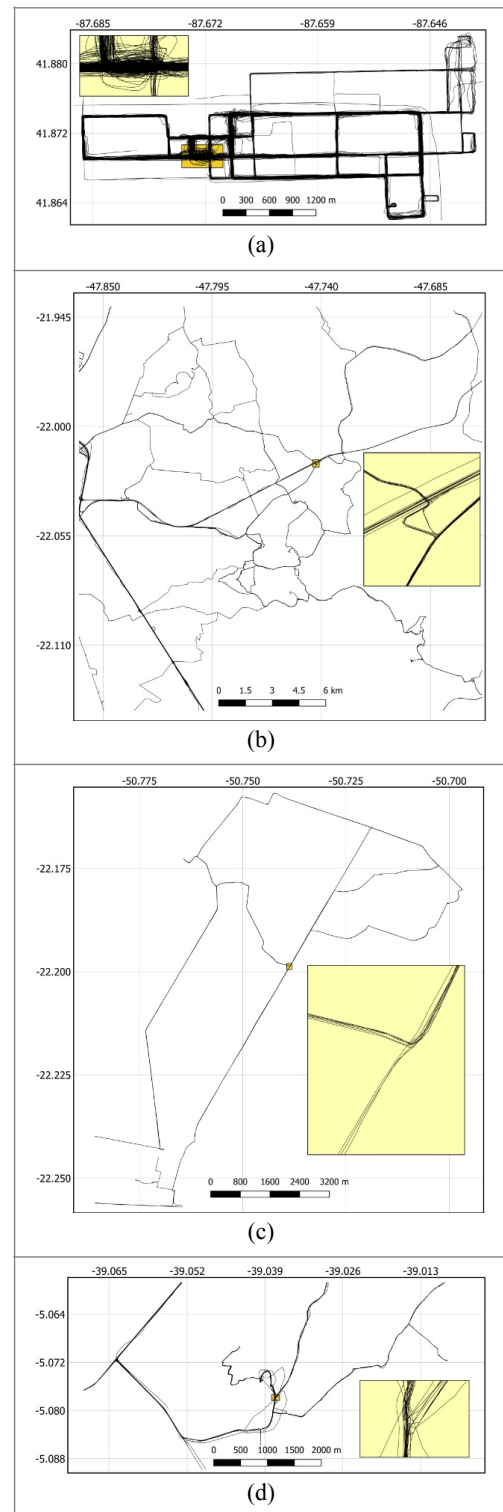
In the next step, the Voronoi diagram for points along road ribbon boundary polylines is constructed (Figure 3a). However, as in the generalization step the number of polyline vertices has been reduced considerably and there is naturally no regular spacing between them, it is necessary to produce a dense sequence of points, evenly spaced along the road ribbon boundary polylines, to be used in the construction of the Voronoi diagram (Figure 3a). The point spacing parameter for sampling these points will directly influence the shape of the centerline derived from the edges of the Voronoi diagram. Large values produce serrated appearances, while low values produce smoother road centerlines. After generating the Voronoi diagram, a geometric filtering is applied in order to leave only the edges whose vertices are within the road ribbons, obtaining the segments that describe the road centerlines (Figure 3b). Usually, it is expected that results present some geometric and topological problems that result from the application of the proposed skeletonization method (Figure 3c), which can be compensated by using filtering strategies. The geometric filtering consists of pruning the unwanted branches; this is carried out using the minimum segment length criterion. Topological filtering, on the other hand, involves the removal of duplicate road crossing points (occur usually at road crossings with four or more connections), which are replaced by the midpoint. This provides a description of the road network (Figure 3d).

### 3. RESULTS AND DISCUSSION

The proposed method was evaluated by using four GPS trajectory datasets (Figure 4):

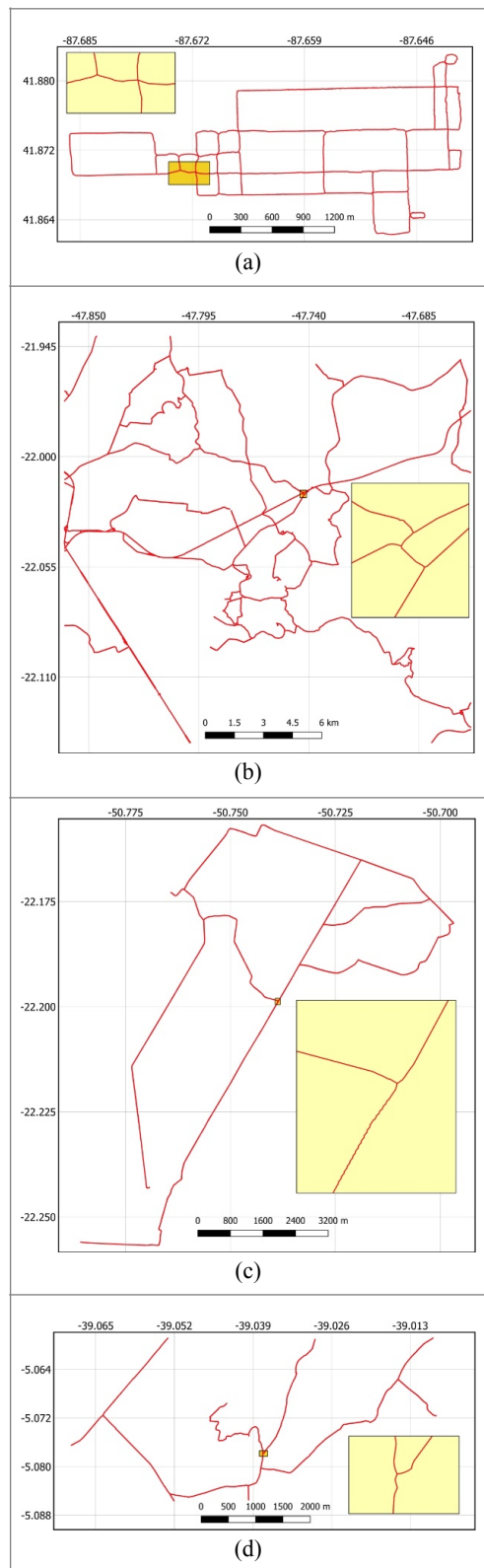
- One of these datasets was collected through GPS receivers installed on university buses in Chicago (USA) and made available to the scientific community by the University of Illinois at Chicago (<https://www.cs.uic.edu/bin/view/Bits/Software>) (Figure 4a);
- Another dataset was collected in a rural area near the city of Presidente Prudente (Brazil) using low cost GPS navigation receivers (Figure 4c);
- Other two datasets were obtained from the OpenStreetMap project (<https://www.geofabrik.de>) (Figure 4b,d), whose test areas are predominantly rural.

The proposed method requires the prior supply of the following thresholds or parameters: parameter for the buffer<sup>+</sup> operation: 5m; parameter for the buffer<sup>-</sup> operation: 5.1m; threshold for the Douglas-Peucker polygonization algorithm: 5m; and parameter for resampling equidistant points along the ribbon polylines, aiming at constructing the Voronoi diagram: 5m. Although the parameter for removing small polygons can be algorithmically determined, until now we set it (400 m<sup>2</sup>) empirically. However, in our experiments the same thresholds and parameters were used to process all trajectory datasets.



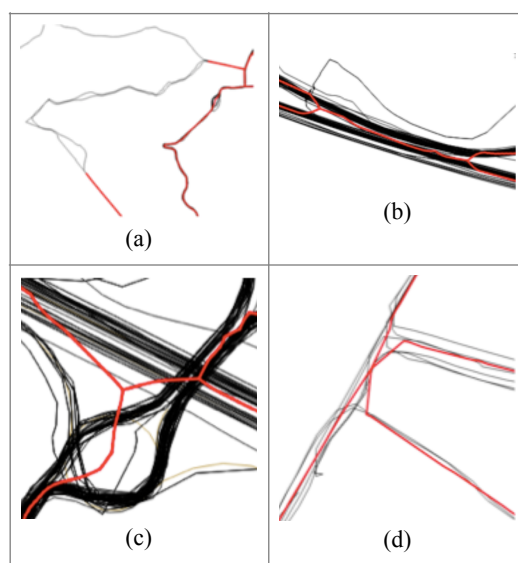
**Figure 4.** GPS trajectory datasets. (a) University of Illinois dataset; (b) OpenStreetMap dataset 1; (c) Presidente Prudente dataset; and (d) OpenStreetMap dataset 2.

The obtained results are presented in Figure 5 and will be discussed below. We visually check the quality of the results, verifying the topological consistency (preservation of road crossings) and the quality of the road tracing.



**Figure 5.** Obtained results. (a) University of Illinois dataset; (b) OpenStreetMap dataset 1; (c) Presidente Prudente dataset; and (d) OpenStreetMap dataset 2.

Visually, it was possible to verify that results are inconsistent when there are not at least three trajectories, as can be seen in Figure 6a, which shows discontinuities in the extracted road (red lines). These problems were already expected in view of the characteristics of the proposed method. Another failure occurred for cases involving very close parallel roads (in the case of these experiments with distances less than 25 meters), which were merged (red lines in Figure 6b). This configuration is relatively common in urban and semi-urban scenarios and the failure identified above can be avoided or minimized by reducing the parameter used in the buffer<sup>+</sup> operation, because in these scenarios there is usually a high density of trajectories. It was also found that in more complex road crossings (Figure 6c,d), such as those involving four or more roads, the fusion of different road crossings into one can occur. Therefore, in these cases, verification by a human operator is recommended.



**Figure 6.** Main failures. (a) Extraction gaps; (b) Road fusion; and (c, d) Fusion of road crossings.

In order to enable a comparison with results found in the literature, the University of Illinois dataset was used for a complementary assessment. The recall, precision and F-score quality indices were used to analyze the results. Recall and precision are measures of completeness and correctness, respectively. F-score is the geometric mean of both quality indexes. To enable the calculation of quality indices, road centerlines made available together with the University of Illinois dataset were used as reference data. The procedures for calculating these quality indexes were the same used by Liu et al. (2012).

Method	Recall (%)	Precision (%)	F-score (%)
Proposed method	72	98	83
Biagioni and Eriksson's method	73	98	83
Qiu and Wang's method	73	97	83

**Table 1.** Comparison of the proposed method with the methods proposed in Biagioni and Eriksson (2012) and Qiu and Wang (2016).

Table 1 presents the quality indexes obtained from the results obtained by the proposed method and by two other methods proposed in Biagioni and Eriksson (2012) and Qiu and Wang (2016). The method proposed by Biagioni and Eriksson (2012) extracts the road centerline through the skeletonization of a trajectory density map. The method proposed by Qiu and Wang (2016) is based on a strategy that combines segmentation and grouping. The results presented in Table 1 show that the performance of the proposed method and the Biagioni and Eriksson's and Qiu and Wang's methods are quite compatible. Only the recall index obtained by our method is slightly lower than those obtained by other methods.

#### 4. CONCLUSIONS

In this article, a method for road network extraction using GPS trajectories is presented and evaluated. The main difference of the proposed method in comparison with existing methods is that all analysis operations are based on the polylines that represent the GPS trajectories. First, morphological analyses (called buffer<sup>+</sup> and buffer<sup>-</sup>) are used to construct an elongated polygon (that delimitates an elongated ribbon) that represents the selected road. Then, a skeletonization technique based on Voronoi diagram is used to extract the road network.

The proposed method was evaluated based on four GPS trajectory datasets. One of these datasets was collected in an urban area of the city of Chicago, USA. The other three datasets were collected in a rural area or in a predominantly rural area. There were some deficiencies in the method that deserve further studies in the future, such as those involving parallel and very close roads and also more complex road crossing (composed e.g. by three or more intersecting roads). The proposed method was also compared with existing methods in the literature and the obtained results showed good consistency between them.

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