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Road network inference through multiple track alignment

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ABSTRACT

Road networks are a critical aspect of both path optimization and route planning. This paper proposes to generate the road network automatically from GPS traces through jointly aligning tracks for each road segment. First, intersections are clustered from turning points where the road users' moving directions change. GPS traces are partitioned into small tracks for individual road segments by directly-connected intersections. The tracks for each road segment are aligned using a greedy method based on successor classification. A "forward-track" procedure is proposed to locate a warp path through jointly traversing all tracks in a way which keeps the points associated by the path element spatially close to each other. This involves an iterative procedure to cluster successor points on the tracks. The warp path produced during the alignment is used to average the tracks as the geometric representation of the road segment, and to analyze the velocity variation along the road segment. Experimental results show our method outperforms other existing methods in producing no spurious road edges and more accurate geometric road representation.

1. Introduction

As Global Positioning System (GPS) devices have been used ubiquitously in the last decades, geographical data is much more easily obtainable from a variety of road users, such as vehicle drivers, cyclists and pedestrians. This abundance of GPS-derived geospatial data has stimulated intensive research activities in Geographical Information Science (GIS). Road networks are generated and updated from the trajectories of the road users (Haklay and Weber, 2008; Haklay, 2010; Biagioni and Eriksson, 2012b). The spatio-temporal patterns of urban traffic congestions have been unveiled to assist urban planning, traffic control and Location-Based Services (LBS) (Herrera et al., 2010; Z. Wang et al., 2013; Castro et al., 2012). Researchers in both industrial and academic fields have shown great interest in city mobility analysis, which provides useful information for public transportation systems, bicycle-sharing system and electric vehicle charing system (Semanjski and Gautama, 2015; Lopez Aguirre et al., 2015; Zheng et al., 2008).

This paper focuses on the topic of automatically generating the road network from GPS traces. Road networks are essential elements of both path optimization and route planning (Syberfeldt and Persson, 2009; Schultes, 2008; Niehoefer et al., 2009; Morris et al., 2004). Existing road maps are mostly constructed from mobile mapping vehicles (Kukko et al., 2007). However, the road maps are updated relatively infrequently using the mobile mapping campaigns because they are expensive. Moreover, they do not provide real-time traffic-related information, such as traffic density. Satellite and Unmanned Aerial vehicle (UAV) images are also used to generate road networks at specific areas. They are not commonly used in big areas

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because of their high cost. Nowadays, digital road maps have been popularly derived from crowd-sourced GPS-derived geospatial data.

Some researchers generate the geometric representation of the roads as a whole from all of the GPS traces firstly, and explore the topology of the roads after the geometry extraction (Davics et al., 2006; Biagioni and Eriksson, 2012b; Chen and Cheng, 2008). Other researchers prefer analyzing the road topology before the geometry inference. They first extract intersections from the GPS traces, segment the GPS traces for individual roads, and produce the geometric representation for each road segment (Fathi and Krumm, 2010; Edelkamp and Schrödl, 2003; Karagiorgou and Pfoser, 2012; Xie et al., 2014, 2015).

In this paper we follow the same work flow as in our previous work (Xie et al., 2015). We first detect intersections from turning points using the moving direction change. We then explore the connectivity of the intersections using all of GPS traces and utilize the intersection connectivity to segment the traces into small track pieces for individual road segments. For each road segment, we first detect the abnormal tracks through track clustering, and calculate its geometric representation by aligning the normal tracks. The main contribution of this paper is a novel method for multiple track alignment. We propose a greedy method to simultaneously align multiple tracks at once, instead of in a pairwise fashion as in our previous work. A "forward-track" procedure is proposed to locate a good warp path through the local dissimilarity matrix, instead of using the "backtrack" procedure through the overall dissimilarity matrix to find the optimal warp path as DTW does. This reduces the computational cost of "back-tracking" the minimal overall dissimilarity. Moreover, instead of finding the next element of the warp path from all adjacent cells of the current element, we propose to limit the candidate cells in the local dissimilarity matrix by classifying the *successors*. The point associations built by the track alignment are used to infer the geometric representation of each road segment, and analyze the velocity variation along it.

The remainder of the paper is organized as follows. In the next section, we introduce the related work. In Section 3, we give the overview of our method, followed by track clustering in Section 4. In Section 5, we detail our method of multiple track alignment. Section 6 shows our experimental results.

2. Related work

In literature, there exists several different approaches for automatically generating road segments from raw GPS traces. Depending on their algorithmic foundations, these approaches can be organized into the following categories:

- *Curve fitting methods.* Edelkamp and Schrödl (2003) employ a K-means algorithm to cluster the data points of raw GPS traces based on a distance measure. The cluster seeds are merged to road segments, and the precise centerline for each segment is generated from the GPS data points corresponding to it using a weighted least squares fitting. Worrall and Nebot (2007) cluster GPS data into regions of similar position with similar headings, and apply non-linear least squares fitting to exact arcs and lines from the cluster data.
- *Trace merging methods.* Cao and Krumm (2009) propose to clarify the GPS traces using simulations of physical forces among the traces, which reduces the effects of GPS noise, and merge the cleaned GPS traces greedily into a graph. Edges from each raw GPS trace are added to the graph, unless an edge with similar location and bearing already exists in the graph under construction. Intersections are then detected from the generated graph. A very similar method is used by Niehoefer et al. (2009), which merges each new trace to an existing map and updates the position of existing roads. Karagiorgou and Pfoser (2012) use a speed threshold in combination with a change in direction to detect the turn samples from GPS traces. They cluster the turn samples into intersection nodes, and bundle the trajectories between the intersections to merge them into road segments.
- *KDE-based methods.* These methods first divide the geographical area into a fine grid of cells, and then estimate Kernel Density (KD) of the data points of GPS traces for each cell. Davics et al. (2006) produce a binary representation of the traces by thresholding on the KD Estimation (KDE). A contour follower is applied on the binary image, so as to extract closed polygons which describe the road regions' outline. The road centerlines are obtained by producing a Voronoi graph of the contours describing the road edges. Instead of a simple threshold, Biagioni and Eriksson (2012a) apply a gray-scale skeletonization technique to extract a threshold-free skeleton from the KDE, so as to achieve both high accuracy and high coverage of road map. Y. Wang et al. (2013) apply a KDE-based approach to update the map using crowd-sourced GPS data. Most of KDE-based algorithms do not function well at the areas where the road users do not traverse often.

All of the methods mentioned above suffer from producing spurious road edges from high-error GPS traces. In our earlier work, we proposed to infer the topology of the road network through intersection identification, and extract the geometric representation of each road segment through track alignment (Xie et al., 2015). We used pairwise track alignment with a "stretch and then compress" strategy to build *one-to-one* associations among the points of the tracks. This method outperformed the existing methods in producing much less spurious road edges. But its "compress" procedure removed the overlapped points, leading to detailed information loss.

In this paper we propose a novel method to align multiple tracks by establishing *many-to-one* associations among the points of the tracks, without removing any point from the tracks. Experimental results show that our proposed method produces more accurate geometric representation, even when the sampling rates of the tracks are very different. Biagioni and