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Understanding the tourist mobility using GPS: How similar are the tourists?

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ABSTRACT

The emergence of the motilities paradigm places tourism at the core of social sciences. Thus, understanding the tourist mobility is fundamental for both tourism management practice and tourism research. This study proposes a heuristic method that combines dynamic time warping and the earth mover's distance, to accurately measure the similarity of tourist trajectories. A case study at Xiamen University Campus was conducted to estimate the performance of our proposed method, and the results of two experiments suggest that our method has better measurement accuracy and noise resistance than current methods. Furthermore, our method has vast potential applications in the fields of personalized service, tourism attraction marketing and management.

1. Introduction

Tourism studies have generally been regarded as the periphery discipline of mainstream social sciences (Hannam, Butler, & Paris, 2014; Harrison, 2017), as tourism is often considered as a spillover of daily life (Zheng, Huang, & Li, 2017). The emergence of the "new motilities paradigm" makes it possible to move tourism studies from the margins of social science to its core (Coles & Hall, 2006; Hannam et al., 2014; Harrison, 2017; Wilson & Hannam, 2017), and academics have been increasingly involved in studying tourist mobility (Asero, Gozzo, & Tomaselli, 2016; Bauder & Freytag, 2015; Domínguez-Mujica, González-Pérez, & Parreño-Castellano, 2011; Hannam et al., 2014; Shoval, McKercher, Ng, & Birenboim, 2011; Tchetchik, Fleischer, & Shoval, 2009; Wilson & Hannam, 2017; Zheng, Huang, et al., 2017). In addition, the recent development of tracking technologies makes it possible to accurately record the spatial-temporal movement of individual tourists (Birenboim & Shoval, 2016; Shoval & Ahas, 2016; Shoval & Isaacson, 2007a, 2007b). The mass trajectory data provide unprecedented breadth for the continuous observation of tourist mobility and the study of tourist behavior (Lazer et al., 2009). The mining of tourist trajectory data is therefore promising for tourism research (Li, Xu, Tang, Wang, & Li, 2018).

However, the same movement can be represented as myriad different discretized trajectories, making it difficult to analyze increasingly large volumes of trajectory data (Toohey & Duckham, 2015). Measuring trajectory similarity has thus become one of the most important types of tourist trajectory data mining. In addition, as many studies showed that the trajectory similarity can reflect the tourist similarity to a great extent (McKercher, Shoval, Ng, & Birenboim, 2012; McKercher & Lau, 2008; Rivera, Croes, & Zhong, 2016) and identified its fundamental role in tourism marketing and personalized recommendation (Bekk, Spörrle, & Kruse, 2015; Grinberger, Shoval, & McKercher, 2014; Lew & McKercher, 2006; Orellana, Bregt, Ligtenberg, & Wachowicz, 2012). Trajectory similarity measurement has played a significant role in various applications, such as marketing (Hui, Fader, & Bradlow, 2009; Seiler & Pinna, 2017; Zubcsek, Katona, & Sarvary, 2017), urban planning (Gonzalez, Hidalgo, & Barabási, 2008; Song, Qu, Blumm, & Barabási, 2010) and transportation (Joh, Arentze, Hofman, & Timmermans, 2002; Mao, Zhong, Xiao, & Li, 2017; Zhang et al., 2011). And a multitude of shape-based and time-based methods have been designed to assess the similarity of two trajectories (Yuan & Raubal, 2014).

In the past few years, although the application of tourist trajectory data in tourism study has occasioned an extensive body of literature (Bauder, 2015; Bauder & Freytag, 2015; De Cantis, Ferrante, Kahani, & Shoval, 2016; East, Osborne, Kemp, & Woodfine, 2017; Grinberger et al., 2014; Hallo et al., 2012; McKercher et al., 2012; Zheng, Huang, et al., 2017), little work has been done to assess the similarity of tourist trajectories. Compared with general trajectories, tourist trajectories have peculiar traits (Kemperman, Borgers, Oppewal, & Timmermans, 2003), which have significant implications for measuring their similarity. We analyzed the existing methods and identified a series of possibilities to be considered for better measuring the similarity of tourist trajectories.

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(1) The tourist trajectory is essentially high-dimensional data containing both spatial and temporal attributes because the tourist behavior always occurs in the dimensions of spatial and temporal (Huang & Wu, 2012; Lamsfus, Wang, Alzua-Sorzabal, & Xiang, 2014). The temporal information contained in the trajectory may be especially important for identifying tourist behavior (Birenboim, Anton-Clavé, Russo, & Shoval, 2013; Kang, 2016; Kemperman et al., 2003; Pettersson & Zillinger, 2011; Xia, Zeephongsekul, & Packer, 2011). Increasing attention has been paid to quantifying the similarity between two spatial-temporal trajectories (Ying, Lu, Lee, Weng, & Tseng, 2010). However, regarding the temporal characteristics of trajectories, most studies focus more on the speed of the trajectories and do not consider the duration time at the points of interest (POIs). However, the time spent at a POI may provide a great deal of information on the behavior of tourists (e.g., POI preference) (Xia et al., 2011).
(2) Tourist trajectories are not completely accurate in most cases because of sensor noise and other factors, such as the weak and unstable signals of location positioning systems. Many methods have been designed to filter this noise (Zheng, 2015); even so, it is difficult to ensure that all of the noise points are eliminated. Thus, the noise resistance should be considered while measuring the similarity of tourist trajectories. However, comparatively little attention has been given to this issue.

Acknowledging the limitations of the existing methods, we combine dynamic time warping (DTW) and the earth mover's distance (EMD) to create a heuristic method (D&E). DTW has been proven to be a significantly robust distance measure for calculating spatial similarity (Keogh & Ratanamahatana, 2005; Salvador & Chan, 2007). EMD was first introduced to compare two grayscale images with blurring or local deformations (Peleg, Werman, & Rom, 1989), and is widely regarded as an excellent method for evaluating similarity between two multi-dimensional distributions and as having good noise resistance (Fu, Liu, & Deng, 2006; Rubner, Tomasi, & Guibas, 2000). Given the advantages of these two methods, we use DTW to evaluate the spatial similarity of the tourist trajectories and apply EMD to calculate the temporal similarity of the tourist trajectories—specifically, the similarity of the duration time spent at POIs. This combination is particularly intriguing given that EMD characteristics make up for the limitations of DTW.

A case study at Xiamen University (XMU) Campus, China was conducted to assess the performance of the proposed method. The movement information and demographic information of 56 tourists were collected using GPS and questionnaires, respectively. The results of the experiments suggest that our method has better measurement accuracy and noise resistance than other methods. Furthermore, our method has vast potential applications in the fields of personalized service, tourism attraction marketing and management. This study thus contributes to expanding the potential application of tourist mobility under the circumstances of big data era, and improves the measurement accuracy and noise resistance by proposing a more appropriate trajectory similarity measuring method.

The remainder of this study is structured as follows. Section 2 introduces the relevant literature about the trajectory similarity measurement. The methodological framework and heuristic method (D&E) is proposed in Section 3. Section 4 designs two experiments to evaluate the measurement accuracy and noise resistance of D&E. We further discuss the application of D&E in personalized services, tourism attraction marketing and management in Section 5. Finally, Section 6 gives the conclusions and future work in this direction.

2. Literature review

As an important field in tourism research, the study of tourism nobilities has attracted substantial attention from both academics and practitioners (Hannam et al., 2014; Harrison, 2017). The focus of tourism mobility is fundamental for both tourism management practice and tourism research (Xia et al., 2010; Xia et al., 2011; Zheng, Huang, et al., 2017). In addition, with the recent development of tracking technologies, the mass spatial-temporal trajectory data of individual tourists can be collected accurately (Shoval & Isaacson, 2007a), which provides unprecedented promise for tourism research. Increasing attention has been paid to the application of tourist trajectory data in tourism study, such as behavior analysis (Bauder, 2015; De Cantis et al., 2016; East et al., 2017; McKercher et al., 2012, 2015), tourism consumption (Grinberger et al., 2014), tourist management (Hallo et al., 2012) and location prediction (Zheng, Huang, et al., 2017).

However, while tourist trajectory similarity measurement is an important aspect of tourist trajectory data analysis whose fundamental role in tourism marketing and personalized recommendation has been well demonstrated (Bekk et al., 2015; Grinberger et al., 2014; Lew & McKercher, 2006; Orellana et al., 2012), it is among its least researched phenomena. Seeking to address the limitations of existing studies, we were inspired by methods applied in other fields, such as marketing, urban planning and transportation.

The similarity measurement of moving object trajectories is an important class of trajectory data mining, and numerous methods have been proposed in previous studies. Early studies focused more on the spatial characteristics of trajectories—that is, the shaped-based similarity of trajectories. The classical Euclidean distance (ED) is regarded as the most straightforward method, which measures the similarity by adding up the distances between each corresponding pair of points in the trajectories (Yuan & Raubal, 2014). Yanagisawa, Akahani, and Satoh (2003) improved the efficiency of shaped-based methods by putting forward an efficient indexing method. However, these methods are not suitable for most real-world applications, as they require that the two compared trajectories contain the same number of points. Improvements were made in subsequent studies. Lin and Su (2005) introduced a more effective method to compare spatial shapes of trajectories without considering the sequences of points. Li et al. (2008) proposed the hierarchical-graph-based similarity measurement framework with consideration for the hierarchy property of geographic spaces. Wang and Liu (2012) designed a two-phase algorithm to retrieve the most similar trajectories efficiently, with consideration for the user's preference. However, shape-based methods focus on the geometric characteristics of trajectories and eliminate the temporal characteristics (Ying et al., 2010). While it is common for the tourist trajectory to be essentially high-dimensional data containing spatial-temporal attributes (Huang & Wu, 2012), the temporal information contained in the trajectory may be especially important for a fuller understanding of tourist behavior (Birenboim et al., 2013; Kang, 2016; Kemperman et al., 2003; Pettersson & Zillinger, 2011; Xia et al., 2011).

To address the limitations of shape-based methods, various exploratory analyses on measuring spatial-temporal similarities have been developed that consider the role of temporal attributes in trajectories. The Fréchet distance performs well with even the most widely varying sampling rates and trajectory lengths because of considering the location and sequence of the points along the trajectories (Alt & Godau, 1995). However, this method is susceptible to displacements and outliers (Toohey & Duckham, 2015; Yuan & Raubal, 2014). The longest common subsequence (LCSS) allows for the elimination of outliers through finding the longest common subsequence in a set of trajectories to match the trajectories (Maier, 1978). However, this method cannot distinguish trajectories with similar common subsequences but different gap sizes (Chen, Özsu, & Oria, 2005), and outliers in trajectories may also significantly affect the exploration of movement patterns; thus, LCSS is not ideal for comparing human trajectories (Yuan & Raubal, 2014). In contrast, DTW is appropriate for dealing with the trajectory similarity of human motions (Yuan & Raubal, 2012): it measures trajectory similarity by warping the trajectories in a non-linear way, and performs well with trajectories of different lengths and varying sampling rates. However, DTW places more emphasis on

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