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Mapping the Spatial Distribution Patterns of Personal Time Spent Based on Trip Purpose

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ABSTRACT

Understanding the spatial distribution patterns of the time spent by people based on their trip purpose and other social characteristics is important for sustainable urban transport planning, public facility management, socio-economic development, and other types of policy planning. Although personal trip survey data includes travel behavior and other social characteristics, many are lacking in detail regarding the spatial distribution patterns of individual movements based on time spent, typically due to privacy issues and difficulties in converting non-spatial survey data into a spatial format. In this article, geospatially-enabled personal trip data (Geospatial Big Data), converted from traditional paper-based survey data, are subjected to a spatial data mining process in order to examine the detailed spatial distribution patterns of time spent by the public based on various trip purposes and other social characteristics, using the Tokyo metropolitan area as a case study.

KEYWORDS

Geospatial Big Data, Geospatially-Enabled Personal Trip Data, Spatial Distribution Patterns, Time Spent, Trip Purposes

INTRODUCTION

Traditional paper-based personal trip survey data, also known as travel diaries, contain a variety of useful information regarding travel behavior, mode of transportation, and transit information, as well as other social characteristics that are highly useful for transportation planners, policy makers, and other socio-economic planners. In addition to such information, many urban and transportation planners, public facility managers, and emergency response teams still require other spatiotemporal data such as the individual movement of people for specific time intervals, actual travel distance and route taken by various transportation modes, where and how much time is spent for various trip purposes, travel volume by routes, etc. Moreover, travel patterns are shaped by both different landscape patterns and different trip purposes (Antipova, Wang, & Wilmot, 2011; Boarnet & Crane, 2001; Fan & Khattak, 2008). The relationship between travel behavior and spatial characteristics has been examined in several studies, such as those investigating the effects of urban spatial structure on

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individual behavior (Horton & Reynolds, 1971), correlation or causality between the built environment and travel behavior (Handy, Cao, & Mokhtarian, 2005), the effect of spatial characteristics on commuting distances (Manaugh, Miranda-Moreno, & El-Geneidy, 2010), the built environment and network travel (Brownstone, 2008; Cao, Mokhtarian, & Handy, 2009), socio-economic factors and travel behavior (Lu & Pas, 1999), and the effect of the built environment on travel behavior (Zhang, Nasri, Hong, & Shen, 2012). Although numerous researchers have explored the relationship between travel and activity locations on both macro and micro levels (Banister, 1992; Cervero & Kockelman, 1997; Naess & Sanberg, 1996; Schönfelder & Axhausen, 2010), studies examining the time spent and spaces visited by individuals for different activities are very rare due to difficulties in converting non-spatial information into spatial information.

Therefore, the conversion of paper-based personal trip data into a geospatially-enabled spatiotemporal dataset is essential in order to understand changes in travel behavior over space and time. Although information regarding human mobility can be acquired using mobile call data recorded via wireless communication and networking technology, such data are not sufficient to make accurate spatial decisions in detailed transportation planning, public facility management, disaster mitigation, and emergency preparedness, largely due to the lack of detailed information with respect to trip purpose, mode of transportation, gender, occupation, etc. Therefore, personal trip survey data are still required for governmental decision-making purposes. Nowadays, it is possible to convert paper-based personal trip data into geospatially-enabled spatiotemporal personal trip data by applying modern geospatial technologies. However, due to the variety of attribute information available (e.g., gender, occupation, trip number, sub-trip number, longitude, latitude, mode of transportation, etc.) at a high temporal resolution (i.e., minute scale) in geospatially-enabled spatiotemporal personal trip data, the dataset itself is huge, with all data linked to each other in a phenomenon known as Geospatial Big Data.

Moreover, the handling of Geospatial Big Data requires considerable computational power and sophisticated spatial data-mining techniques. Spatial data-mining, which is essentially the process of identifying geographical knowledge or spatial distribution patterns from a large amount of georeferenced data, plays an important role in GIS (Geographical Information System) by enabling users to understand spatial relationships between geographical entities or features, to find spatial distribution patterns, to cluster similarities, and to predict future events. On the other hand, a proper urban planning process requires information regarding how people travel based on their age, occupation, and trip purpose, how long they spend at a location based on trip purpose, where most people travel, etc., in order to build an accessible city and improve urban quality of life (Banister & Bowling, 2004). In the present study, the authors used geospatially-enabled personal trip (PT) data to examine how individuals spend their time (e.g., a no-movement event such as staying at home, or inside shopping centers, schools, etc.), based on a trip purpose code with start and end locations. Finally, the extracted dataset was imported into a GIS in order to identify the spatial distribution patterns of time spent by individuals based on trip purpose and other social characteristics. The paper comprises two main sections. Firstly, the authors explain the applied conversion of paper-based personal trip data into a geospatially-enabled personal trip dataset, with details provided regarding data structure and attribute information; secondly, the authors explain the spatial data-mining process employed to extract data regarding continuous time spent for various trip purposes to generate the various maps that can be used in further GIS analysis.

STUDY AREA

The authors used geospatially-enabled PT data acquired in 2008 for the Tokyo metropolitan area, which includes Saitama, Chiba, Kanagawa, and 23 Tokyo wards. Figure 1 shows the study area, indicating the administrative units, transportation network, and populated places. Approximately 600,000 personal trips were analyzed for single weekday activities and movements recorded every minute.