INVESTIGATING THE RHYTHMS OF HUMAN MOVEMENTS IN GENEVA LAKE REGION USING MDC DATA

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ABSTRACT:

Movement data are becoming extensive and comprehensive with the advent of GPS (global positioning system) and pervasive use of smartphones, which has led to an increasing rate of studies about movement such as mobility pattern of oil spills, taxies, storms and animals. Studying the movement of people has long been the topic of much thought and debate among researchers within the field of transportation, social issues, and policy. One of the basic prerequisites for studying human movement behavior is modeling the movement, which show how people move so that the effect of different variables can be revealed. For this purpose, this research intends to deploy the concept of activity space (i.e., the part of the space in which a person is active) and its determinants to display the trajectory of individuals, and then modeling the effect of different variables on human mobility behavior. This study explores the effect of time (movement on weekends and weekdays) and demographic (age, gender, occupation state) factors on the characteristics of human mobility pattern and analyzes the extent to which the mobility pattern of different group of people is related to time by using Swiss human movement sample dataset, called MDC. These movement characteristics can be used later in a wide range of applications, such as predictions, urban planning, and traffic forecasting.

1. INTRODUCTION

Human mobility plays an important role in the study of traffic forecasting, disease spreading, urban planning, and in the general science and engineering of smart cities (Luo, Cao et al. 2016). In the past, most of the efforts to understand the human movement were based on the data collected by questionnaires (Yamamoto and Kitamura 1999), which were expensive, not big enough and led to a time-consuming, inefficient process. However, the amelioration of Web and mobile technologies yields a set of reliable and cost-effective data sources that has triggered studies of human mobility patterns (Shi, Chi et al. 2015).

Human mobility is restricted by a multitude of demographic factors such as age, gender, occupation, and income. In addition, temporal order (e.g., weekends and weekdays) are considered to an important impact on individual movement behavior (Yuan, Raubal et al. 2012). Due to the inherent inconsistency of movement patterns on weekdays and weekends, it is necessary to explore human mobility under different temporal orders.

This paper aims to explore the correlation between demographic variables (age, gender, and occupation) and human movement pattern with time perspective by exploiting Swiss human movement sample dataset, i.e., Mobile Data Challenge (MDC) dataset, in Geneva Lake Region.

2. METHODOLOGY

Activity space is defined as a geographic coverage of an individual's movement trajectory by considering visited places and taken routes that helped her get to her destinations (Lee, Voss et al. 2016). There are several related concepts, such as the action space (Horton and Reynolds 1971), the awareness space (Brown and Moore 1970), or space-time prisms (Hagerstrand 1970).

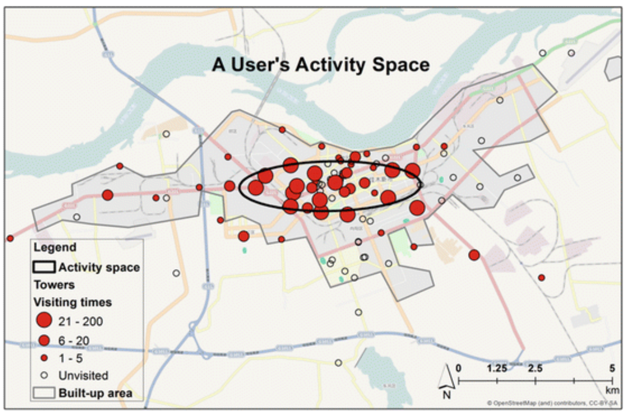

Figure 1. deviational ellipse (Wang, Kang et al. 2015)

The approximation and measurement of activity space depict the basic characteristics of activity space (size, shape, etc.). Historically, activity space is measured based on two types of methods: Eclipse-based representation (Figure 1), e.g., standard deviational ellipse, the radius of gyration (Song, Qu et al. 2010) and network-based representation (e.g., road networks) (Sherman 2011). We adopt the ellipse-based method to better characterize the geometric properties of activity spaces. In order to identify the characteristics of activity space, the following determinants have been employed:

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Area: It indicates the extent of the activity space (Newsome, Walcott et al. 1998), and is used to depict the dispersion of the visited locations (Schönfelder and Axhausen 2003). The area of the standard deviation ellipse is calculated as follow:

$$area = \pi ab \quad (1)$$

where a is the semi-major axis and b is the semi-minor axis of the ellipse.

Shape index (1-eccentricity): As users' trajectories are approximated as ellipses, the movement eccentricity represents how much a particular activity space's shape deviates from a circular shape:

$$e = \sqrt{1 - \left(\frac{b}{a}\right)^2} \quad (2)$$

For instance, if $e \approx 1$, it is highly possible that the particular person mostly moves between popular pegs of her life such as work and home; therefore, the shape of activity space is close to a regular straight line rather than a circle (Yuan and Raubal 2016). Here, we use 1-eccentricity to represent the extent to which an activity space deviates from a straight line. The higher the value of shape index, the more scattered is a user's visited places and the more is the shape of her activity space like a circle rather than a thin ellipse.

3. RESULTS

3.1 MDC Dataset

In January 2009, Nokia Research Centre Lausanne and its Swiss academic partners designed the Lausanne Data Collection Campaign (LDCC) to create large-scale mobile data researcher sources. Data was collected using Nokia N95 phones and around 185 volunteers (38% male and 62% female) who lived near Geneva Lake contributed in this project over a period of one year. Although myriad types of data were recoded from the smartphones of volunteers, this paper has used demographic information of participants (age, gender, and the occupation), and their location information produced by cell phone's GPS (time, longitude, latitude) in every 5 seconds (Kiukkonen, Blom et al. 2010, Laurila, Gatica-Perez et al. 2012).
In the following section, users' trajectories are separated based on the days of the week and then the determinants of the activity space are calculated for each individual. Subsequently, the average and standard deviation of the mentioned parameters in each group is used for detecting the impact of time on users' movement.

3.2 Correlation between days of the week and activity space

Isaacman deployed median daily range and maximum daily range to understand the effect of time on the movement of people in America using mobile phone data (Isaacman, Becker et al. 2011). In this research, activity space is fitted to the maximum travel distance of some users in Switzerland instead of the median of the daily range.
According to the area of activity spaces (Tables 1, 2 and Figure 2), users have on weekends bigger activity spaces than on weekdays. It shows that users tend to travel to further places on weekends, which could be due to the closure of schools and having more free time during weekends. In addition, users have a higher standard deviation of the area on weekends that indicates bigger diversities among users' movement behavior on weekends (Table 2). One reason of this difference might be stemmed from the idea that the majority of users tend to spend their weekend at home but those who travel are eager to go to further and scattered destinations (Isaacman, Becker et al. 2011). However, in contrast to Yuan's results in 2013, the difference between the shape index of the users' activity space on weekends and weekdays is not too much (Yuan 2013).
Note that general holidays are omitted from Table 1 and 2.

Days of the week	No[1]. users	Avg[2] area	Std[3] area	Avg SI	Std SI[4]
Saturday	152	1206356320	1735113197	0.1108	0.1127
Sunday	150	1230619443	1812527016	0.1282	0.1355
Monday	150	540205863	1132220687	0.085	0.1128
Tuesday	152	610718147	1329976328	0.1016	0.129
Wednesday	153	565862949	946240586	0.0883	0.1014
Thursday	152	519474182	768785652	0.099	0.116
Friday	152	760972719	1247755746	0.1099	0.1253

Table 1. Average and standard deviation of area and shape index of users' activity space grouped by days of the week

Week	No. users	Avg area	Std area	Avg SI	Std SI
weekends	152	1412443579	1790098291	0.1357	0.123
weekdays	155	784907146	1041589367	0.1219	0.124

[1] Number of
[2] Average of
[3] Standard deviation of
[4] Shape index

Table 2. Average and standard deviation of area and shape index of users' activity space grouped by weekdays and weekends

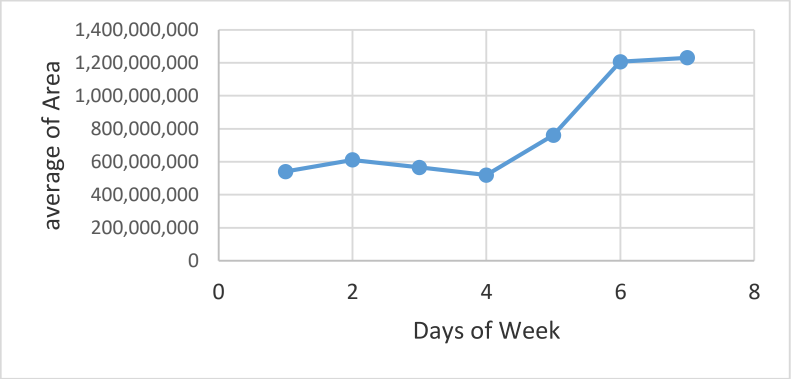

Figure 2. The relation between days of the week and users' activity space

Many other variables could affect the relationship between time and the determinants of activity space. For example, as Crane showed, having a car, job position, family and marital status, etc., have an impact on the relationship between gender and determinants of activity space (Crane 2007). Therefore, in the following sections, in order to investigate the relationship between demographic variables (gender, age, and occupation), days of the week and users' movement behavior, users in the MDC dataset were first classified with regard to their gender, age, and occupation. Then the effect of time on the determinants of the activity space of individuals' trajectories in each demographic group was analyzed.

3.3 Correlation between gender, days of the week and activity space

As seen in Tables 3, by calculating the parameters of activity space for each user in male and female group and then averaging them, it is determined that both men and women have higher values for their activity space area and shape index on weekends, which demonstrate that people on weekends, have a longer distance travels, visit more scattered places, and shape of their activity space is far from the straight line. However, with regard to Table 4 and the greater standard deviation of the average of men's activity space determinants, the impact of time (days of the week) on their movement behavior is much higher than that of women. Men experience further and more dispersed travels during weekends. Moreover, having greater standard deviation of activity space's determinants shows that the difference in their mobility behaviour is much higher on weekends compared to women. This difference could be attributed to the fact that most of men tend to spend their weekend near their home, but those minorities who travel have very long journeys with scattered destinations.

gender	Week (female)	No. users	Avg area	Std area	Avg SI	Std SI
Female	Weekends	54	1067216087	1430578855	0.1272	0.1219
	Weekdays	55	734150519	978573888	0.1154	0.1274
male	Weekends	95	1544937519	1986419847	0.1461	0.1456
	Weekdays	74	694896844	1003542127	0.1022	0.1274

Table 3. Average and standard deviation of area and shape index of user's activity space grouped by days of the week

Gender	std (avg area)	Std (avg SI)
Female	235512921	0.0083
Male	601069525	0.0311

Table 4. Effect of weekdays on the activity space of men and women.

3.4 Correlation between age, days of the week and activity space

Individuals in all age groups have higher activity space's area and shape index on weekends. It indicates that individuals have more distant and scattered travels and thus active lifestyle on weekends. Moreover, it is observed that the physical shape of activity space also deviates more from a straight line at weekends. The standard deviation of the determinants of the activity space is also higher on weekends, and thus the difference in mobility behavior of individuals is greater (Tables

5 to 11). As Table 12 shows, the highest value for the standard deviation of the average of activity space determinants belong to those who are 28 to 33 years old and the lowest amount is dedicated to people aged 16 to 21 years and also those over 50 years old. It is well understood from the mentioned results that time has the greatest impact on the movement behavior of people aged 28 to 33 years and have the least effect on people aged 16 to 21 and over 50. Being unemployed and, as a result, having unlimited time for more distant trips among these two groups of people and on the other hand, being employed and therefore having restricted time opportunities for those between 28 and 33 years can be considered as one of the reasons for these results.

Week (age16-21)	No. Users	Avg area	Std area	Avg SI	Std SI
Weekends	13	1039875920	1110898094	0.0993	0.092
Weekdays	13	970745566	1738028615	0.1519	0.1127

Table 5. Average and standard deviation of area and shape index of users between 16-21 based on days of the week.

Week (age 22-27)	No. Users	Avg area	Std area	Avg SI	Std SI
Weekends	56	1208791969	1427396533	0.1125	0.1079
Weekdays	56	666359556	799505045	0.0918	0.1075

Table 6. Average and standard deviation of area and shape index of users between 22-27 based on days of the week.

Week (age 28-33)	No. Users	Avg area	Std area	Avg SI	Std SI
Weekends	46	2134567844	2656874695	0.1439	0.1152
Weekdays	49	1005903159	1299951503	0.1004	0.1062

Table 7. Average and standard deviation of area and shape index of users between 28-33 based on days of the week.

Week (age33-38)	No. Users	Avg area	Std area	Avg SI	Std SI
Weekends	19	1182588267	1321342023	0.1996	0.1495
Weekdays	20	663117506	726213938	0.158	0.142

Table 8. Average and standard deviation of area and shape index of users between 33-38 based on days of the week.

Week (age 39-44)	No. Users	Avg area	Std area	Avg SI	Std SI
Weekends	13	1154948493	1121658229	0.1432	0.1102
Weekdays	13	608855113	572571472	0.1355	0.1474

Table 9. Average and standard deviation of area and shape index of users between 39-44 based on days of the week.

Week (age 45-50)	No. Users	Avg area	Std area	Avg SI	Std SI
Weekends	2	910481240	634954914	0.0656	0.032
Weekdays	2	439812267	389629272	0.0371	0.0234

Table 10. Average and standard deviation of area and shape index of users between 45-50 based on days of the week.

Week (more than 50)	No. Users	Avg area	Std area	Avg SI	Std SI
Weekends	2	541437216	533857349	0.0471	0.01
Weekdays	2	296899361	299658176	0.0854	0.0168

Table 11. Average and standard deviation of area and shape index of users more than 50 based on days of the week.

Age group	Std (avg area)	Std (avg SI)
21-16	48882542	0.0372
27-22	383557638	0.0147
33-28	798086453	0.0307
38-33	367321298	0.0294
44-39	386146332	0.0054
50-45	332813222	0.0202
more than 50	172914376	0.0271

Table 12. Comparison of the effect of weekdays on users' activity space with different age group.

3.5 Correlation between occupation, days of the week and activity space

As is shown in tables 13 to 17, in all working groups the area, shape index and the standard deviation of the activity space determinants were higher on weekends due to the closure of schools, universities, and workplaces which let people have more free time on weekends. Thus, individuals tend to visit more distant places and their destinations are spread out and are not restricted to the pegs of their life. In addition, the result of the comparison of the effect of time on the mobility behavior of individuals with different working status is shown in Table 18. With regard to the value of standard deviation for people in different working groups, it can be concluded that the change in time (days of the week) has the greatest effect on the mobility behavior of employed people and has the least effect on unemployed people. One of the interpretations might be lack of sufficient time opportunity for staff to travel around on weekdays.

Week (working full time)	No Users	Avg area	Std area	Avg SI	Std SI
Weekends	82	1661450051	1986095364	0.1609	0.2062
Weekdays	84	841776417	934879644	0.1347	0.2027

Table 13. Average and standard deviation of area and shape index of full-time job users grouped based on weekdays.

Week (working part-time)	No Users	Avg area	Std area	Avg SI	Std SI
Weekends	13	2290298195	2528344571	0.1122	0.0759
Weekdays	14	1091894605	1719317169	0.1273	0.1513

Table 14. Average and standard deviation of area and shape index of part-time job users grouped based on weekdays.

Week (not working)	No Users	Avg area	Std area	Avg SI	Std SI
Weekends	7	536953830	529956734	0.1311	0.1244
Weekdays	7	383026570	358675271	0.1015	0.0847

Table 15. Average and standard deviation of area and shape index of not working users grouped based on weekdays.

Week (studying full time)	No Users	Avg area	Std area	Avg SI	Std SI
Weekends	41	1007158761	1097836709	0.1083	0.1119
Weekdays	41	774265424	1103522258	0.1094	0.1189

Table 16. Average and standard deviation of area and shape index of full time studying users grouped based on weekdays.

Week (housewife)	No Users	Avg area	Std area	Avg SI	Std SI
Weekends	5	573722326	477361844	0.0997	0.0087
Weekdays	5	122863208	156767262	0.098	0.1036

Table 17. Average and standard deviation of area and shape index of housewife users grouped based on weekdays.

Occupation Group	Std (avg area)	Std (avg SI)
working full time	579596785	0.0185
working part time	847399305	0.0107
not working	108843009	0.0209
studying full time	164680458	0.0008
housewife	318805539	0.0012

Table 18. Comparison the effect of days of week on users with different occupations.

4. CONCLUSION

This paper examines the effect of time (days of the week) on movement characteristics of people and the extent to which it has an impact on different groups of people with a particular same demographic factor (gender, age, and working status). For this, activity space and its determinants (area and shape index) have been deployed to show the extent and the dispersion of movement. The approach was applied on a set the MDC dataset. It was concluded that people have further travels with a more dispersed destination on weekends. Additionally, it has depicted that time has the most effect on the movement behavior of men particularly people aged 28-33 and the least effect on those aged 16-21 and people who are older than 50 years old. We believe that the results of this study have the potential to contribute to the betterment of urban planning, solving social issues and mitigating traffic problems.

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