RAZMERJE MED VZORCI ČLOVEŠKEGA GIBANJA IN TELEKOMUNIKACIJAMI Z UPORABO STRUKTURE GRAFOV

GRAPH-BASED ANALYSIS OF THE CORRELATION BETWEEN MOBILITY AND TELECOMMUNICATION

Roya Esmaeili Tajabadi, Parham Pahlavani, Amin Hosseinpoor Milaghardan

UDK: 621.39:796.012
Klasifikacija prispevka po COBISS.SI: 1.02
Prispelo: 1. 10. 2022
Sprejeto: 27. 2. 2023

DOI: 10.15292/geodetski-vestnik.2023.01.40-57
REVIEW ARTICLE
Received: 1. 10. 2022
Accepted: 27. 2. 2023

IZVLEČEK

Upoštevanje odnosa med vzorci človeškega gibanja in telekomunikacijami v prostoru in kibernetskem prostoru nam pomaga bolje razumeti te vzorce gibanja. V študiji smo raziskovali razmerje med vzorci človeškega gibanja in telekomunikacijami z uporabo strukture grafov. Parametri ustvarjenih grafov, vključno z vozliščem, robom, odstotkom skupnih uteži zanke, uteženim lokalnim gručenjem in uteženim globalnim koeficientom gručenja, so bili izračunani in primerjani s korelacijsko matriko. Nato so bili preučeni učinki oddaljenosti in števila edinstvenih telekomunikacijskih partnerjev. Implementacija predlagane metode na podatkih Mobile Data Challenge (MDC) je pokazala, da več kot je gibanja med dvema specifičnima regijama, več je izmenjave telekomunikacijskih podatkov. Poleg tega se razmerje med številom klicev in številom premikov nekoliko poveča z večanjem razdalje med izvorom in ciljem. Več kot ima posameznik telekomunikacijskih partnerjev, večje je število selitev in večje število regij obišče. Oseba z manj telekomunikacij z bližnjimi območji ima tudi manj gibanja v bližnjih regijah. Nazadnje, struktura gibanja in telekomunikacijski grafi posameznika so podobni – večja kot je interakcija in več kot je povezav med vozlišči enega, več je povezav med vozlišči drugega.

ABSTRACT

Considering the relationship between human movement patterns and telecommunications in space and cyberspace helps us better understand these movement patterns. This study investigated the relationship between human movement patterns and telecommunications using a graph structure. The parameters of the created graphs, including the node, edge, percentage of the loop's total weights, weighted local clustering, and weighted global clustering coefficient were calculated and compared by a correlation matrix. Then, the effects of distance and the number of unique telecom partners were examined. Implementation of the proposed method on Mobile Data Challenge (MDC) data showed that the more the movement between two specific regions, the more the telecommunication exchanged. Furthermore, the ratio of the number of calls to the number of displacements increases slightly with increasing the distance between the origin and destination. The more telecom partners an individual has, the greater the number of displacements and the greater the number of regions that he visits. A person with less telecommunication with nearby areas also has less movement within nearby regions. Finally, the structure of movement and telecom graphs of an individual are similar—the higher the interaction and connections between nodes of the one, the more the connections between the nodes of the other.

KLJUČNE BESEDE

telekomunikacije, človeško gibanje, analiza grafov

KEY WORDS

Telecommunication, Human mobility, Graph analysis

1 INTRODUCTION

In recent years, access to tracking tools such as the Global Positioning System (GPS) and smartphones has led to the advancement of movement data in terms of volume and accuracy, resulting in cheaper, more frequent, and global-scale studies of human movement (Becker et al., 2013). The development of information and communication technologies (ICT), such as mobile phones and the Internet, has also increased communications. Thus, in addition to spatial information, a vast amount of information related to human communication and interaction has been produced (Toole, Herrera-Yaqüe, Schneider, & González, 2015). These interactions and telecommunications can affect face-to-face meetings and travel. As a result, it will affect people's behavior and movement patterns (Aderibigbe, 2021; Baym, Zhang, & Lin, 2004; Turkle, 2012; van den Berg, Arentze, & Timmermans, 2013). Considering the relationship between human movement patterns and telecommunications in space and cyberspace helps better understand these movement patterns (Gao, Liu, Wang, & Ma, 2013; P. Mokhtarian & Salomon, 2002; Senbil & Kitamura, 2003). Moreover, awareness of this relationship can be used in various fields such as placing infrastructures, urban policies and planning, and traffic reduction (Toole et al., 2015). These analyses can also be used in location-based services to send the user advertising messages related to the upcoming location by analyzing people's movement path (Monclar, Tecla, Oliveira, & de Souza, 2009).

In general, human movement is influenced by various internal and external factors. Their interaction creates spatiotemporal patterns in their movement, which indicates how they move (Ceder, 2021; Nathan et al., 2008). Various approaches such as activity space, trajectory, and graph-based methods have been adopted to study and measure movement patterns. The activity space approach has been used to study the geometric parameters of human movement, which indicates the scattering of places in which the person has been present (Wang, Kwan, & Chai, 2018; Zhang, Yang, Zhen, Lobsang, & Li, 2021). For example, Yuan et al. used the three parameters of radius, eccentricity, and entropy of ellipse to investigate the relationship between the frequency of telephone calls and movement (Yuan, Raubal, & Liu, 2012). In addition, spatial data can be traced from GPS points such as car movements that are accurate to about 10 meters. To analyze spatial data, we face various challenges such as the large volume of data, which may include millions of points (Guo, Zhu, Jin, Gao, & Andris, 2012). Besides, in some applications, the main route and trajectory are not essential and are ignored; only the origin and destination are crucial. For example, from the point of view of taxi passengers, only the origin and destination are essential, and the route is not vital. Immigration data, air travel, phone calls, and emails are other origin and destination data (Demissie & Kattan, 2022; Guo et al., 2012; Kim & Cho, 2021). In these cases, origin and destination data analysis is examined as a graph, and the movement is displayed as a set of nodes and edges (Lim, Kim, & Heo, 2019; Saberi, Mahmassani, Brockmann, & Hosseini, 2017).

The idea of movement modeling using graphs or trees is not new (Saberi et al., 2017). However, it has recently been shown that a better understanding of the relationships between places and people and their dependencies can be obtained through network or graph analysis (Batty, 2013; Lim et al., 2019). Using the graph structure, we find out which part of the network influences the other with criteria such as centrality measures (Asgari, Gauthier, & Becker, 2013). Quantitative measures called centrality measures, such as input degree and output degree, are used to evaluate and analyze the spatial structure in graph analysis (Newman, 2008). Saberi et al. compared people's movement patterns in Melbourne and Chicago using the centrality measures of graph analysis of mobile data (Saberi et al., 2017). They concluded that despite the differences in urban structure, human movement patterns in these cities are similar. In another study in Shenzhen, China, an Origin-Destination (OD) graph was created by clustering GPS points of taxis. Then, using parameters such as inflow and outflow, the researchers studied movement patterns and communities in the OD graph (Guo et al., 2012). Another study used clustering-based patterns, centrality graph parameters, and the Marco clustering algorithm to discover the most visited areas and busy tourist routes (Hu, Li, Yang, & Jiang, 2019). Gao et al. formed communities within movement and telecommunication graphs and concluded that people communicate in a spatially adjacent community (Gao et al., 2013).

Despite the importance of studying movement from a graph perspective, the relationship between movement and telecommunication has been scarcely studied from a graph perspective, except in limited cases (Cao et al., 2021; Gao et al., 2013; Saberi et al., 2017). In previous studies, the impact of ICTs such as phone calls, text messages, and Internet usage was considered on mobility indicators such as the number of trips, personal miles traveled (PMT), vehicle miles traveled (VMT), vehicle kilometers traveled (VKT), and the number of commuting trips (Andreev, Salomon, & Pliskin, 2010; Jamal, Habib, & Khan, 2017; Kong, Moody, & Zhao, 2020; Senbil & Kitamura, 2003). The four states in which communication technologies can affect people's movement are substitution, complementarity, neutrality, and modification (Andreev et al., 2010; Mokhtarian, 1990). Depending on the type of activity and the duration of the study, each of the conditions mentioned above may be obtained. For example, Senbil and Kitamura concluded the effect of phone calls on work activities is a substitution, neutral to short-term activities, and complementary to voluntary activities (Senbil & Kitamura, 2003).

In this research, a graph structure was used to investigate the relationship between the movement of individuals in space and their telecommunication in cyberspace. The difference in the strength of the interaction links between pairs of nodes and the parameters showing the graph's structure locally and globally is essential for mobility analysis. Therefore, graph parameters such as flux and clustering coefficient were used in the study. Furthermore, since telecommunication can represent social relations between people, the number of people with whom a person has made telecommunication can define a person's social network (Alessandretti, Lehmann, & Baronchelli, 2018). Therefore, the impact of the number of users with whom one has telecom interactions on the movement graph parameters was also assessed. The Swiss MDC data were used to implement the proposed method. The assessments carried out in this research are as follows:

- Investigating the relationship between the parameters of the graph of human movement in space and the graph of telecommunication in cyberspace
- Comparing the effect of distance on the parameters of movement and telecommunication graphs
- Examining the impact of the number of unique telecom partners of a person on the parameters of the movement graph

The structure of the paper is as follows: Section 2 discusses the data and the study area. The proposed method is presented in Section 3, and its implementation is described in Section 4. Finally, Section 5 presents the discussion and conclusion.

2 DATA AND STUDY AREA

This paper used the MDC dataset related to the Lausanne data collection campaign that was collected in Switzerland around Lake Geneva, from October 2009 to late 2011 (Laurila et al., 2012). The participant were volunteers in the Lake Geneva region who agreed to take part in the project and share their data, mainly driven by selfless interest. The data were collected using Nokia N95 phones, and most of the participants remained in the study for over a year (Laurila et al., 2012). The population included various demographic attributes which were self-reported by the users: gender: (62% male, 38% female), age group (a. 16-21, b. 22-27, c. 28-33, d. 33-38, e. 39-44, f. 45-50, g. more than 50), job type (working full-time, working part-time, not currently working, studying full-time, studying part-time, housewife). The MDC dataset was collected in 31 tables, of which the following three tables have been used:

- gps: locations of each user for about every 5 seconds (GPS)
- calllog: data about phone calls and text messages, including the time of the call or text message and the phone number of the call partner
- records: used to join the other tables by having a unique db-key column

Since this study aimed to investigate the relationship between human movements and telecommunication, each user's stops and displacements were specified. Among the users, 62, with a reasonable spread of phone calls/texts across the study period, were selected to implement the proposed method. The number of calls and messages of the selected users was 5267, and their displacements were 28230.

3 THE METHOD

The graph-based method of examining the relationship between people's movement and telecommunication consists of three parts (Fig. 1). In the first part, the study area is divided into sections. Then, the location of stopping points and the origin and destination coordinates of each person's telecommunication are determined. The movement and telecommunication graphs are created in the next step. In the last step, the parameters of the created graphs are calculated and compared by a correlation matrix. The effect of distance and the number of people the participants have telecommunication with during the project are also examined.

3.1 Preprocessing

First, the study area should be divided into several sections. In this study, urban divisions[1] were used to separate the study area. The stop points and the origin and destination of calls and text messages (defined in Section 3.1.1) were located in 326 areas, so each area was assigned a unique code. Afterward, the area code in which the stop points, the origin, and the destination of each person's telecommunication were located was given to them.

3.1.1 Stop point detection and determining the origin and destination coordinates of telecommunications

In this step, the center coordinates of each person's stop regions are determined to create a movement graph in the next section. A stop region refers to a cluster of GPS points representing a geographic region where the user has stopped for a specific period. Each person's stopping regions are determined by the method presented by (Montoliu & Gatica-Perez, 2010). By clustering each user's GPS points, the points 200 meters

[1] *HOHEITSGEBIET: a German word meaning territory; it is one of the administrative division levels in Switzerland.*

apart at a time distance of 20 min are considered a stop region. Afterward, the center coordinate of each stop region, called the stop point, is determined by averaging the point coordinates in each stop region (Fig. 2).

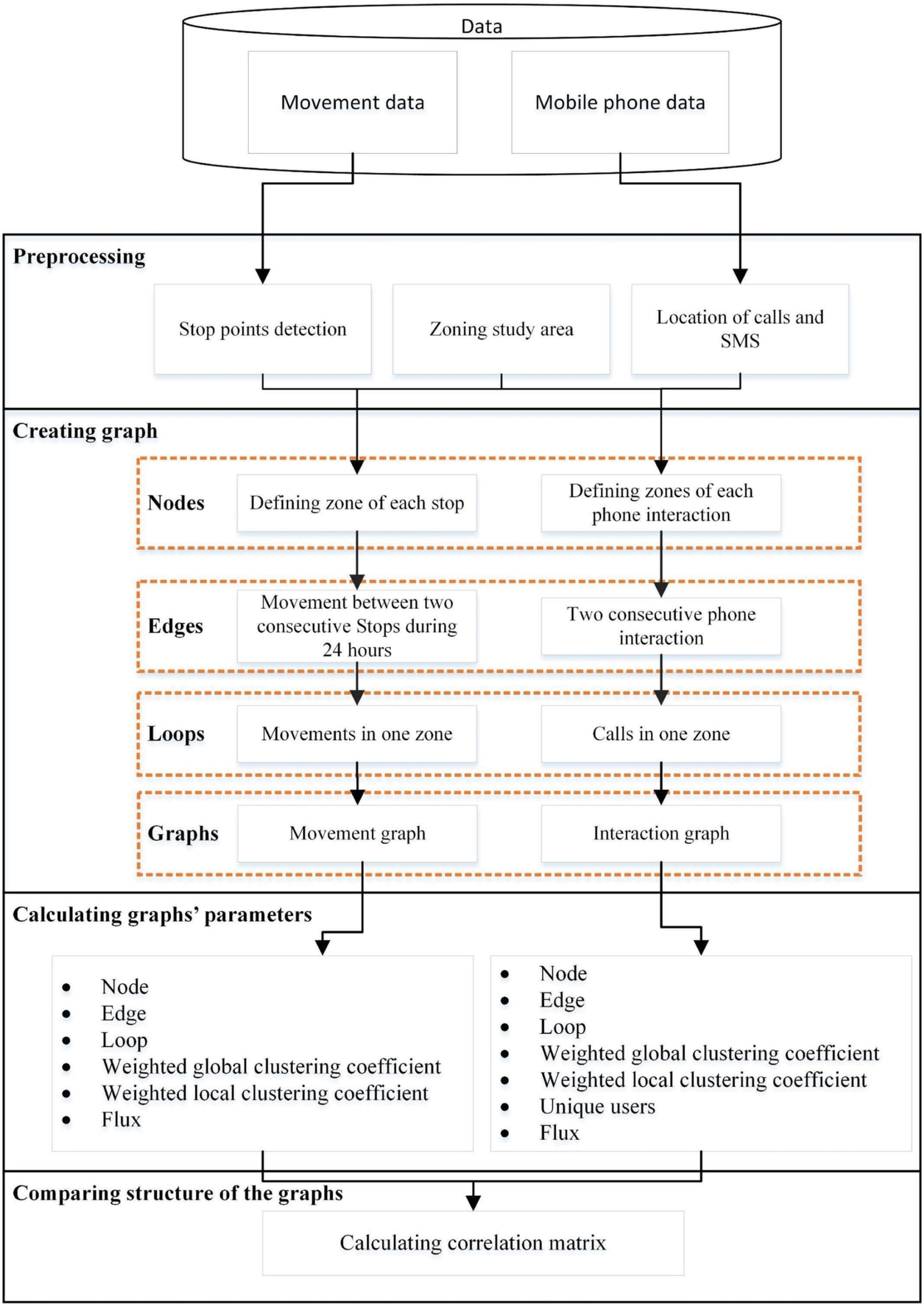


Figure 1: The method.

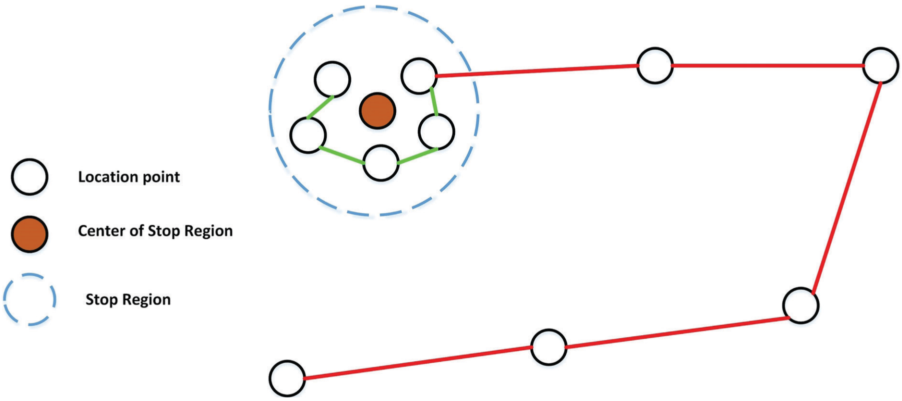


Figure 2: Stop region and stop point detection.

In this step, the origin and destination coordinates of telecommunications, including telephone calls and short messages of individuals, must also be specified to create the next step's telecommunication graph. In other words, it should be determined from which region the phone call or short message was made to which region. The time of each phone call or text message and from which user to which this call was is specified in the dataset. Moreover, each user's position in 5-second intervals is in the GPS part of the dataset. Therefore, with the telecommunication time and the users' location on both sides, telecommunication coordinates are determined separately at the communication time (Fig. 3).

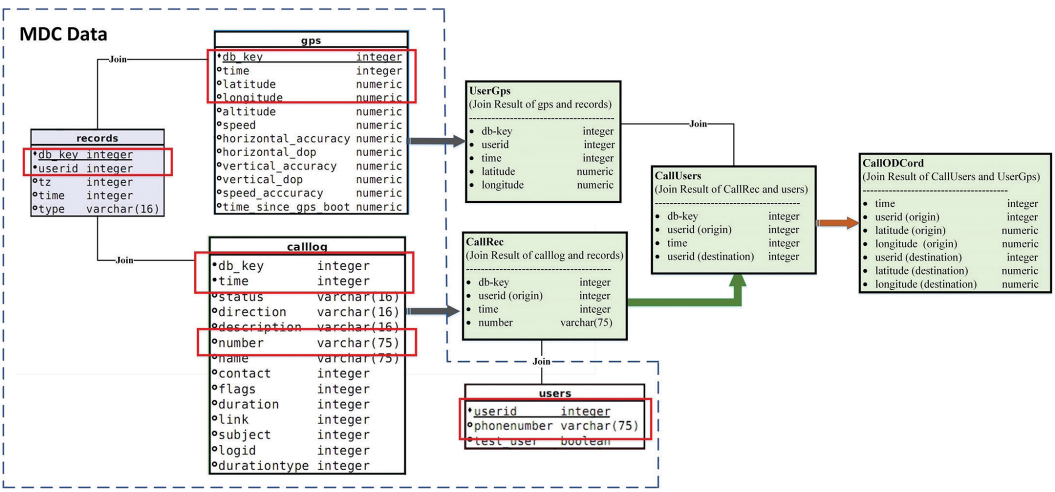


Figure 3: Determining the origin and destination coordinates of telecommunications.

3.2 Constructing the graph

In the previous section, the study area was divided into sections, and the stop point coordinates and the coordinates of the users on both sides of the telecommunications were determined. Therefore, a movement graph was created for each user with the area code of each stop point and the sequence of the stop points in 24-hour intervals. Moreover, having the origin and destination areas, the telecommunication graph was created separately for 62 users.

Graph *G* is a set of nodes (vertex) and edges (edge) and is thus displayed as $G = (V, E)$ (Hu et al., 2019). Edges indicate the connection between the nodes; the edge that connects a node to itself is called a loop. The proximity matrix is used to represent the graph structure. If there is a connection between the two nodes or the same edge, it receives 1; otherwise, it receives 0. In a weighted graph, each edge has a weight calculated according to the type of the graph.

The first step is to make the nodes and the edges between them and determine their weight to create a graph. The nodes are the urban regions where the stops are made in the movement graph, and the edges are the displacements between the nodes. The weights of the edges are also the number of displacements between the nodes. If the displacement occurs within an urban region, two consecutive nodes are the same and form a loop. The number of displacements within each region is also considered the loop's weight.

Each person's telecommunication graph was constructed similarly to the previous method by knowing each telecommunication's origin and destination coordinates. Urban regions in which origins and destinations were located are considered nodes. The edges are the telecommunications between the regions. The weights of the edges are the number of telecommunications between the nodes. If the origin and destination of a call are within the same area, it forms a loop. The number of calls within the region for each region is also considered the loop's weight.

3.3 Calculating graph parameters and the correlation matrix

After creating a weighted graph of each person's movement and telecommunication, the graphs' parameters are calculated. A correlation matrix examines the relationship between the parameters of movement and telecommunication graphs. The Pearson correlation coefficient (r) is used to explore the relationship, the value of which indicates the linear relationship between the two parameters (Taylor, 1990).

The graph parameters that made sense for both the movement and telecommunication graph were selected:

- **Nodes:** In the movement graph, it is equal to the number of unique areas in which the stops occurred. The number of nodes in the telecommunication graph is similar to the number of separate regions where the origin or destination of the calls occurred.
- **Node flux or node strength:** The strength of node *i* is the sum of the weights of all the edges to which the node is attached (Eq. (1)) (Barrat, Barthelemy, Pastor-Satorras, & Vespignani, 2004):

$$s_i = \sum_{j=1}^{N} a_{ij} w_{ij}, \tag{1}$$

where w_{ij} is the edge's weight between nodes *i* and *j*. a_{ij} is the element of the adjacency matrix, which is equal to 1 if there are edges between nodes *i* and *j*; otherwise, it is 0. The node flux in a movement graph equals the number of displacements made from or to that point. It also equals the number of telecommunications from each point and others in the telecommunication graph. This parameter compares each node's strength in two graphs to determine whether there is a relationship between the movements made from an area and the contacts exchanged with it. This parameter is at the scale of a node.

– **Total weight of the graph edges:** The sum of the total weight of the edges in the graph (*S*) is:

$$S = \sum_{i=1}^{N} S_i, \tag{2}$$

where S_i is the flux of the *i*th node. *S* in the movement graph is equal to the total number of transfers, and in the telecommunication graph, it is similar to the total number of calls and text messages.

– **Percentage of loops' total weight:** As mentioned earlier, a loop is an edge that connects a graph node to itself. The total weight of the loops (*L*) and the percentage of the loops' total weight (*L%*) are:

$$L = \sum_{i=1}^{N} a_{ii} w_{ii} \tag{3}$$

$$L\% = \frac{L}{S} \times 100 \tag{4}$$

The weight of each loop in the movement graph equals the number of displacements within an area. *L* in the telecommunication graph equals the number of calls whose origin and destination are located in an urban area. *L%* represents the percentage of the total intra-region displacements in the movement graph and the percentage of the total intra-area telecommunications in the telecommunications graph.

– **Weighted local clustering coefficient (Lc_i):** This index indicates how locally the graph nodes tend to cluster and denotes the formation of groups in the network (Saberi et al., 2017).

$$Lc_i = \frac{N_{CNi}}{N_i}, \tag{5}$$

where N_{CNi} is the number of connected pairs of neighbors of node *i*. N_i is the number of pairs of neighbors of node *i*.

– **Weighted global clustering coefficient (Gc_ω):** The global clustering coefficient parameter indicates the degree of clustering tendency and group and community formation throughout the graph (Saberi et al., 2017). The lower the value of this parameter, the more the spatial distribution of the graph points and the less the connectivity between them. The global clustering parameter is based on transitivity and is calculated as the ratio of triplets on the graph's total number of triplets. The triplet is formed by three nodes connected by two edges (open triplet) or three edges (closed triplet). A triangle consists of three triplets, and each is centered on one of the nodes of the triangle. Since the graphs created for this study are weighted, a generalized version of this parameter called the weighted global clustering coefficient is used (Opsahl & Panzarasa, 2009):

$$Gc_\omega = \frac{\sum_{\tau_\Delta} \omega}{\sum_{\tau} \omega}, \tag{6}$$

where ω is the triplet value and is obtained from the arithmetic mean of the weights of the edges that constitute the triplet. $\sum_{\tau_\Delta} \omega$ is the sum of the values of closed triplets and $\sum_{\tau} \omega$ is the sum of the values of the triplets, whether open or closed.

In addition to creating the movement and telecommunication graph for each user and comparing their structures, a telecommunication graph and a movement graph were formed using the entire telecommunication and movement data of the users. The parameter of Buffer Overlap Area (BOA) was used to compare the degree of geometric similarity of the two graphs:

- **Buffer Overlap Area (BOA):** The area of the overlapping region created by the buffer of the objects is a parameter denoting the degree of geometric similarity between the two objects (Eq. 7) (Fan, Yang, Zipf, & Rousell, 2016; Fan, Zipf, Fu, & Neis, 2014). The closer the value of this parameter to 1, the higher the spatial similarity of the objects.

$$BOA(PL_1, PL_2) = \frac{2A_i}{A_{PL_1} + A_{PL_2}} \tag{7}$$

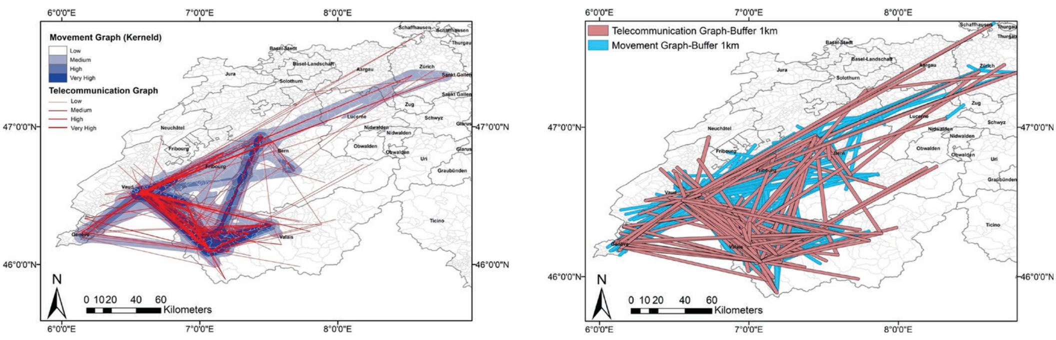
where A_{PL_1} is the buffer area of the first object, A_{PL_2} is the buffer area of the second object, and A_i is the common buffer area.

4 EXPERIMENTAL RESULTS

First, the movement graph and telecommunication graph obtained from the total data of users are examined. Then, the movement and telecommunication graph are formed for each user, and a correlation matrix examines the relationship between their parameters.

4.1 Comparing the movement and telecommunication graphs obtained by the data of all individuals

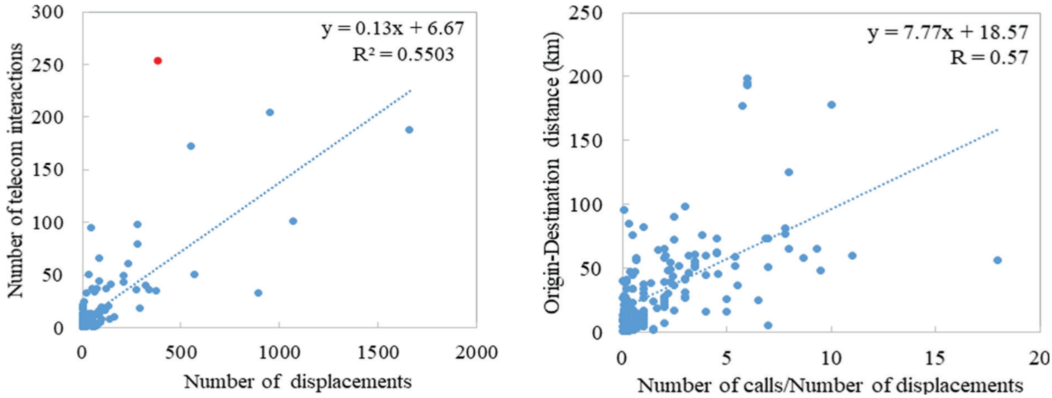
The movement and the telecommunication graph consisting of all individuals' data are depicted in Fig. 4a. As shown in this figure, the range of people's physical space movement overlaps with their telecommunications in cyberspace. Furthermore, to determine the degree of similarity and overlap of the two graphs, the 1-km buffer for both graphs was created, and the BOA degree was calculated (Fig. 4b). The BOA degree of 0.7051 shows the similarity between the two graphs and proves the claim that movement and telecommunication are connected.



(a) (b)

Figure 4: a) Overlapping movement graph and telecommunication graph, b) Movement graph and telecommunication graph with the 1-km buffer, TelecomBufferArea=3254.08km^2, MovementBufferArea=5162.03 km^2, OverlapArea=2967.11 km^2, BOA=0.7051.

Users have moved and made phone calls between 167 pairs of different origins and destinations. The relationship between the number of displacements and telecommunications between each unique source and destination is presented in Fig. 5a. For example, the red dot represents the origin with code 80 to the destination with code 110. It indicates that 254 calls and 377 displacements have been exchanged between these two regions. The graph shows that, to some extent, the more movement between two specific regions, the more the exchanged telecommunications . Besides, the ratio of the number of calls to the number of displacements increases slightly with increasing the distance between the origin and destination (Fig. 5b).



(a) (b)

Figure 5: a) Correlation of the number of displacements and telecommunications between each unique source and destination – each dot represents a specific source and destination; for example, the red dot represents the origin with code 80 to the destination with code 110 b) the correlation of the ratio of the number of calls to the number of displacements and the distance of the origin and destination.

4.2 Comparing the movement and telecommunication graph formed for each user

Table 1: Correlation matrix of movement and telecommunication graph parameters. Absolute values equal to or greater than 0.5 show significant relationships. Positive relationships are in blue, and negative ones are in red.

Parameters	Unique Users	Movement node	Telecom node	Total weight of the movement graph edges	Total weight of the telecom graph edges	Inner movement (%)	Inner interaction (%)	Weighted global clustering coefficient - Movement Graph	Weighted global clustering coefficient - Telecom Graph	Mean weighted local clustering - Movement Graph	Mean weighted local clustering - Telecom Graph
Unique Users	1.00	**0.55**	0.27	**0.50**	0.33	-0.28	-0.27	0.05	0.01	0.44	0.34
Movement node	**0.55**	1.00	**0.54**	**0.50**	0.31	-0.29	-0.19	-0.03	0.10	0.44	0.40
Telecom node	0.27	**0.54**	1.00	0.22	0.35	-0.25	-0.02	0.03	-0.05	0.13	0.12
Total weight of the movement graph edges	**0.50**	**0.50**	0.22	1.00	**0.64**	-0.07	-0.13	-0.01	0.04	**0.95**	0.47
Total weight of the telecom graph edges	0.33	0.31	0.35	**0.64**	1.00	-0.08	0.01	-0.01	-0.02	0.45	0.14
Inner movement (%)	-0.28	-0.29	-0.25	-0.07	-0.08	1.00	0.60	**-0.76**	-0.44	-0.08	-0.13
Inner interaction (%)	-0.27	-0.19	-0.02	-0.13	0.01	**0.60**	1.00	-0.44	-0.26	-0.19	-0.13
Weighted global clustering coefficient - Movement Graph	0.05	-0.03	0.03	-0.01	-0.01	**-0.76**	-0.44	1.00	**0.62**	0.02	0.00
Weighted global clustering coefficient - Telecom Graph	0.01	0.10	-0.05	0.04	-0.02	-0.44	-0.26	**0.62**	1.00	0.08	0.05
Mean weighted local clustering - Movement Graph	0.44	0.44	0.13	**0.95**	0.45	-0.08	-0.19	0.02	0.08	1.00	**0.52**
Mean weighted local clustering - Telecom Graph	0.34	0.40	0.12	0.47	0.14	-0.13	-0.13	0.00	0.05	**0.52**	1.00

After creating the graphs of movement and telecommunication for each person, the parameters of the graph expressed in Section 3.3 were calculated for each graph. Afterward, the correlation matrix was formed (Table 1).

The absolute r values equal to or greater than 0.5 show highlighted strong relationships. Based on the r-value, there are 10 significant relationships, three of which are between the movement graph parameters that are depicted in Fig. 6. The other seven significant relationships are between the movement and telecom graph, which generally show the correlation between the structure of the movement graph and the users' telecom graph, depicted in Fig. 8, Fig. 9, and Fig. 10, and explained more in Section 4.2.1.

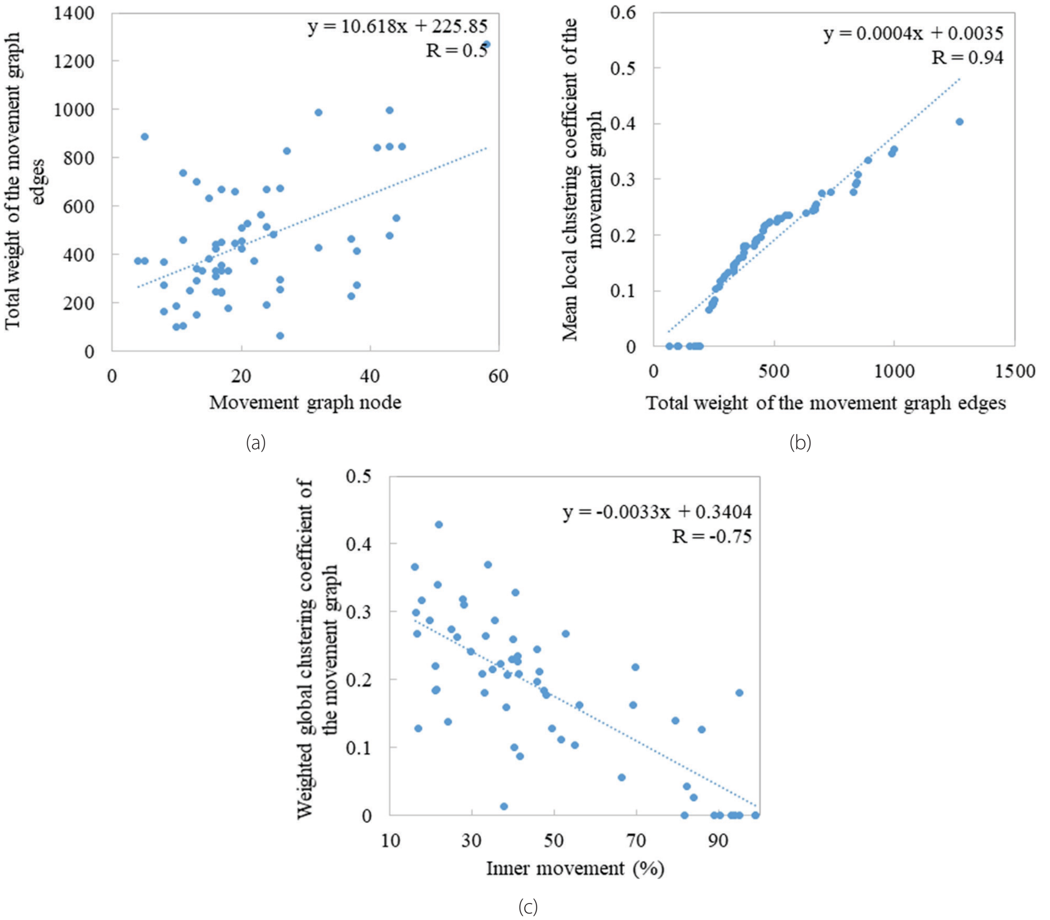


Figure 6: a) Correlation between the movement graph nodes and total weights of the movement graph edges, b) correlation between the total weights of the movement graph edges and the mean local clustering coefficient of the movement graph, c). correlation between the percentage of inner movement and the weighted global clustering coefficient of the movement graph.

The number of movement graph nodes is directly related to the weighted sum of its edges (Fig. 6a). In other words, the more movements people have, the more unique area(s) they move. This can depend on people's careers. For example, someone who is a full-time employee may only travel between home and work during the day and have less displacement compared to a person who is a bike-delivery, moves between various places, and makes more moves. The greater the weighted sum of the edges of people's movement graph, the higher the average local clustering coefficient of the movement graph nodes (Fig. 6b). In other words, the more movements people have, the more locally connected the nodes of the movement graph are. Inner region movements are inversely related to the weighted global clustering coefficient of the movement graph (Fig. 6c). This means that the higher the percentage of displacements within regions, the less clustered and connected the nodes of the movement graph. For example, a person who lives in the city center or in a place where most of his daily needs are met by local centers may need less travel to other areas, and most of his/her movements are within his/her residence region.

4.2.1 Comparing the structure of the graphs

The graphs' structures were compared by the parameters mentioned in Section 3.3. Moreover, the impact of the number of unique telecom partners of a person on the nodes and edges of the movement graph was also determined.

First, the graphs' average flux in every 326 unique regions was calculated to compare the average movements and telecommunications in different areas (Fig. 7). The average flux of the movement and the average flux of individuals' telecommunications for each region are directly related. Therefore, the higher the average flux of movement in a region, the more the average flux of telecommunication. In other words, the more the movement from one area, the more the established telecommunications.

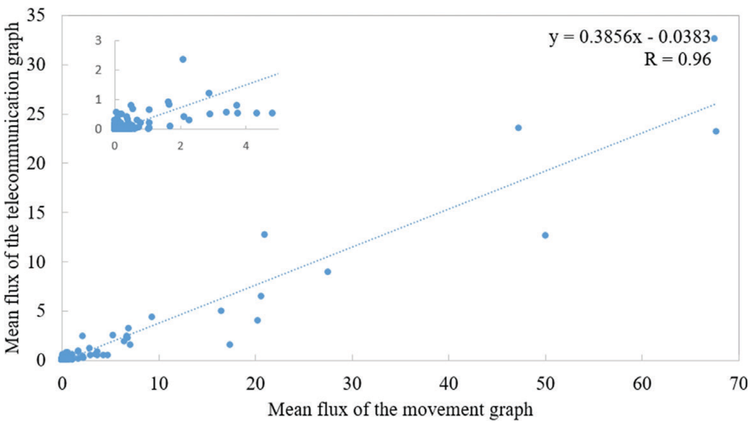
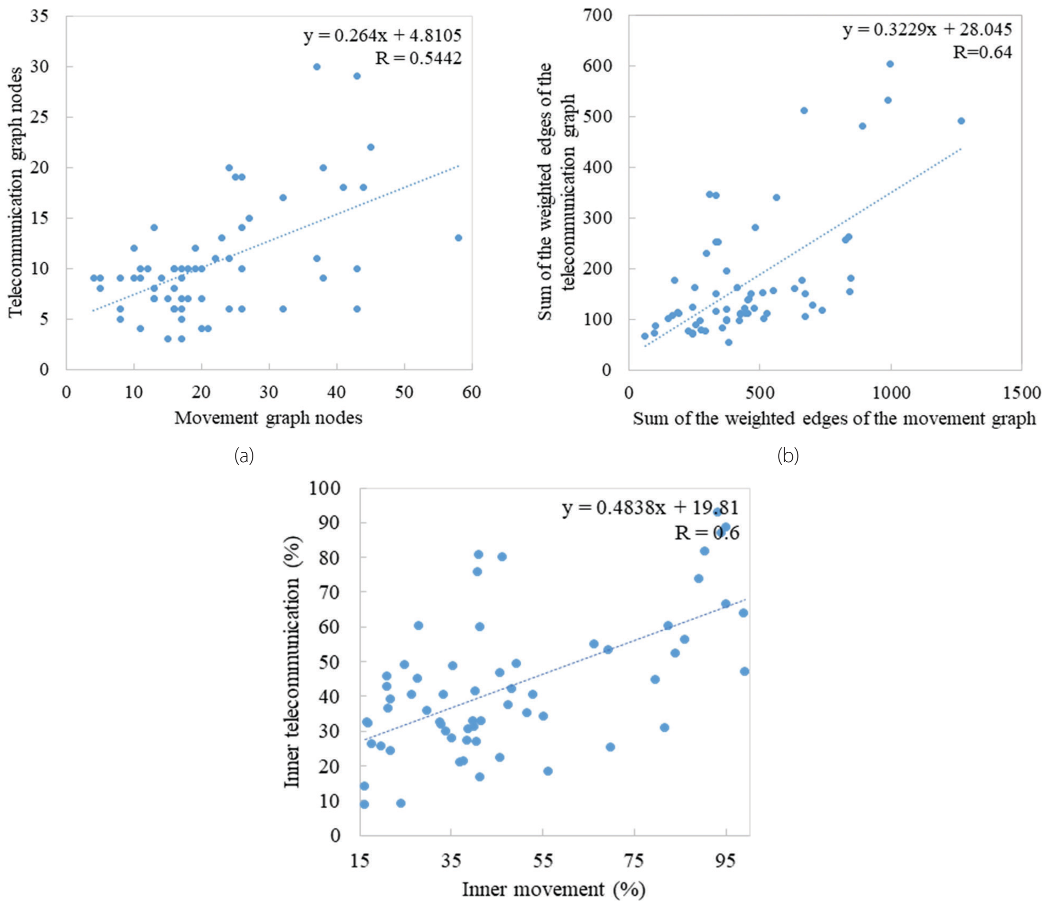


Figure 7: Correlation between the mean flux of the movement graph and the telecommunication graph of each of the 326 regions.

There is a direct relationship between the number of nodes of the movement graph and the individuals' telecommunication graph (Fig. 8a). In other words, a person who has geographical connections to more areas also has telecommunications to more areas. The value of this correlation is not very large due to the multifactorial nature of human behavior. However, this relationship also demonstrates that the geographical scope of human telecommunication and mobility are related.

As well as, Fig. 8b shows there is a direct relationship between the sum of the edges' weights of each person's movement and telecommunication graphs. In other words, as the number of spatial movements increases, the number of telecommunications also rises. People with more calls, text messages, and cyberspace activity are expected to have more spatial transfers.

Furthermore, intra-area displacements and intra-area telecom are directly related (Fig. 8c). Even, regions' movements, which are generally related to daily needs such as shopping, are affected by telecommunications between people and their neighbors. In other words, a person with less telecommunication with nearby areas also has less movement within nearby regions. Therefore, as much as communication can affect long-term shifts, it also affects short-term shift movements.

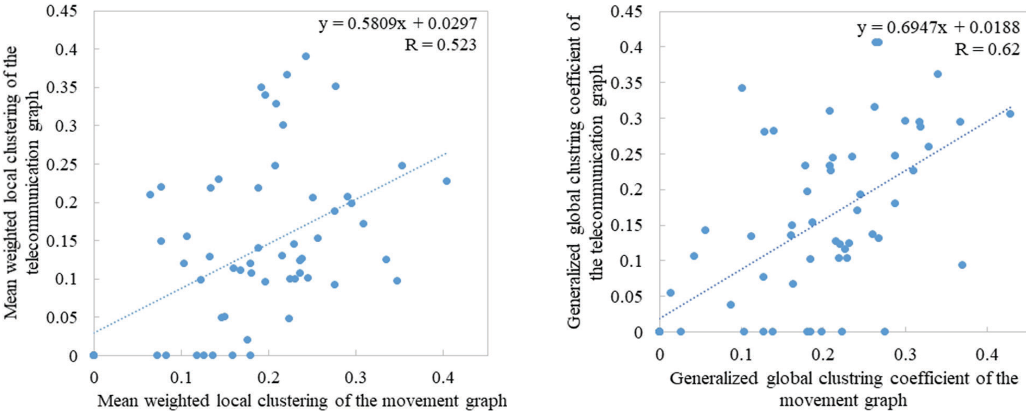


(a) (b) (c)

Figure 8: a) Correlation between the telecommunication graph nodes and the movement graph nodes, b) Correlation between the total weight of the telecommunication graph edges and the total weight of the movement graph edge, c) Correlation between the percentage of the inner movement and the percentage of the inner telecommunication of each user.

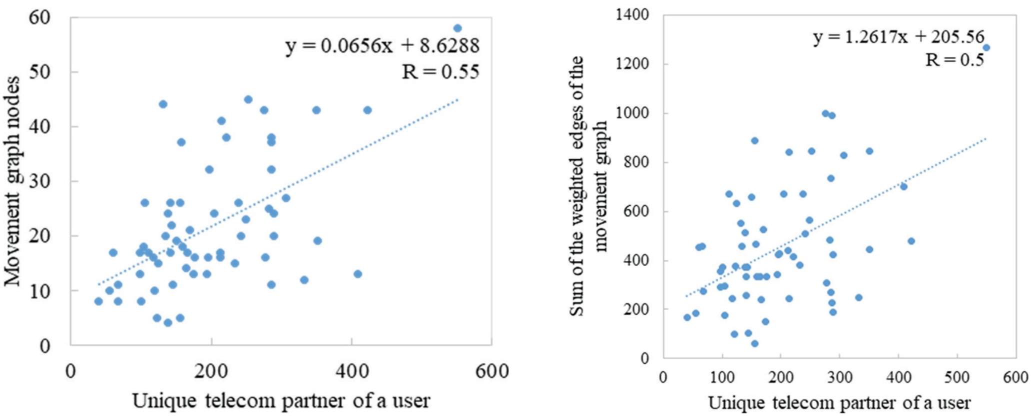
The mean weighted local clustering parameters of the movement and telecommunication graphs have a somewhat positive relationship, suggesting that the more the nodes are locally connected and forming groups in one, the more they are locally connected and forming groups or communities in the other (Fig. 9a).

Weighted global clustering of the movement and telecommunication graphs have a positive relationship (Fig. 9b). This metric generally shows the general structure of both graphs. The limited telecommunication network indicates the limitation of individual movement. In other words, the scatter of one's nodes means the spread of the other's nodes.



(a) (b)

Figure 9: a) Correlation between the mean weighted local clustering of the movement and the telecommunication graph. b) Correlation between the generalized global clustering coefficient of the telecommunication and the movement graph.



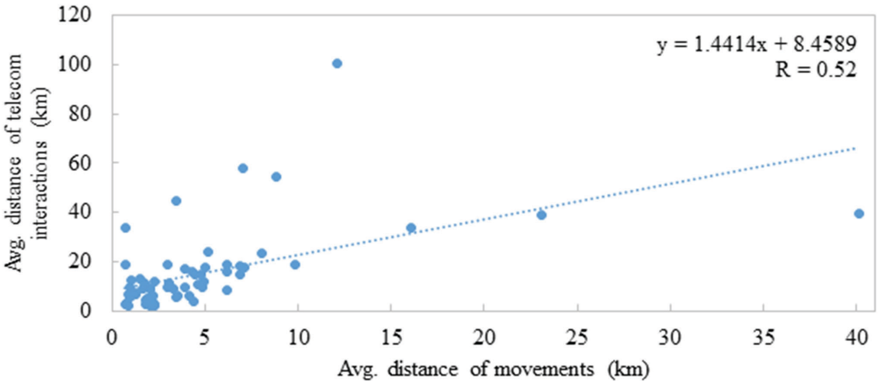
(a) (b)

Figure 10: a) Correlation between the unique telecom partner of a user and the movement graph nodes, b) correlation between the unique telecom partner of a user, and the sum of the weighted edges of the movement graph.

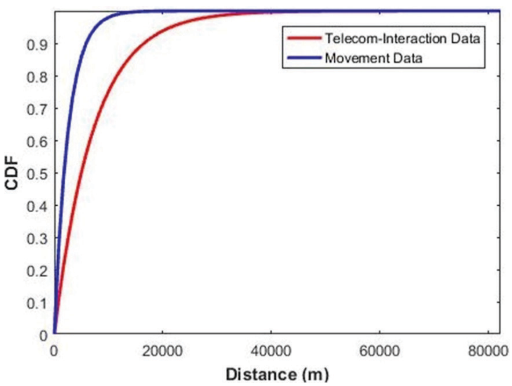
The effect of the number of unique people that a user has telecommunication interactions with on the movement was examined. The number of nodes and the total weight of the edges of the movement graph are directly related to the number of unique telecom partners of a person (Fig. 10a, Fig. 10b). As a result, the more people an individual is connected with, the greater the number of displacements and the greater the number of regions visited. Since telecommunication can be a representative of social interactions, a person who telecommunicates with more people can somehow be considered an extrovert (Lucas, Diener, Grob, Suh, & Shao, 2000). Therefore, this result can be in line with the results of other research noting that extroverted people who are more connected with people tend to explore diverse and more places (Alessandretti et al., 2018).

4.2.2 The effect of geographical distance on the movement communication and telecommunication

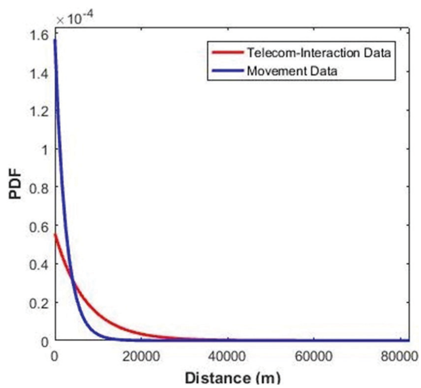
The average movement distance of each person and the average distance of the origin and destination of each person's telecommunication were calculated (Fig. 11a). The value of *r* equal to 0.52 indicates a direct relationship between these two parameters; as the distance between movements increases, the average telecommunication distance rises. This result and the relationship between the number of node graphs (Fig. 8a) show that the degree of dispersion of the range of movement is related to the geographical extent of individuals' telecommunication interactions.



(a)



(b)



(c)

Figure 11: a) The average distance of consecutive movements and the average distance of telecom interactions of each user, b) CDF of movements and telecommunication interaction, c) the PDF of movements within the space, and the PDF of telecommunication interactions across cyberspace.

Cumulative Distribution Functions (CDF) of movements and telecommunication interaction are depicted in Fig. 11b. Nearly 90% of telecommunication interactions occur across distances of less than 20 km. Almost 90% of movements occur within distances of less than 6 km (Fig. 11b). In Fig. 11c, the

Probability Distribution Function (PDF) of movements within space is compared with their telecommunication interactions across cyberspace. The distributions' shape shows that distance's effect on movements is more significant than telecommunication interactions. Furthermore, there is a distance decay effect on both space and cyberspace. Hence, people tend to move and communicate in spatial proximity.

5 DISCUSSION AND CONCLUSION

This article proposed a graph-based method to investigate the relationship between the ICT structure in cyberspace and mobility in the physical world. The proposed method was implemented on the MDC data of Switzerland. First, the movement graph and telecommunication graph obtained from the total data of users were created. A comparison of the two graphs showed that the more the movement between two specific regions, the more the exchanged telecommunications. Besides, the ratio of the number of calls to the number of displacements increases slightly with increasing the distance between the origin and destination. This suggests that for long distances, people prefer phone calls to face-to-face meetings.

Second, the movement and telecommunication graphs were created for each user. The structure of these graphs was compared, and the effect of geographical distance on these graphs was investigated. Therefore, the parameters of the created graphs were calculated, including the node, edge, percentage of the loop's total weights, weighted local clustering, and weighted global clustering coefficient. Afterward, the correlation matrix was formed for the mentioned parameters and the number of unique telecom partners. According to the r-value, in addition to the relationships between movement and telecom graphs, there were three significant relationships between movement graph parameters. The more movements people have, the more unique areas they move, and the more locally connected the nodes of the movement graph are. Furthermore, the higher the percentage of displacements within regions, the less clustered and connected the nodes of the movement graph.

The results showed the correlation between the structure of the movement graph and the users' telecom graph. The average flux of movement and telecommunications for each region indicated that the more movement is made from or to an area, the more telecommunications are to or from it. People with more displacements and visited areas also have more calls and text messages. The global interactions between the nodes in the movement and telecommunication graphs are also the same. Hence, the individual with more groups in the movement graph tends to form more groups or communities in the telecommunication graph. Moreover, the number of nodes and the total weight of a user movement graph edges are directly related to the number of unique telecom partners. As a result, the more telecom partners a user has, the greater the number of displacements and visited regions will be.

The effect of geographical distance on movement and telecommunication was examined. The degree of dispersion of the movement range turned out to be related to the geographical extent of the individuals' telecommunications. The farther people move, the more distant telecommunications they have. Moreover, there was a positive relationship between inner-area movement and telecommunications. Hence, the person with more telecommunication interactions with people within the area also has more inner movements. Third, the mean weighted local clustering coefficient indicated that the nodes' tendency to form local groups is nearly identical in both graphs.

Overall, people's spatial mobility and their telecommunication with regions were well shown in this study using graphs. It was also possible to study the relationship between different areas in space and cyberspace locally and globally. Since the data in this study were related to more than one year, the relationship between movement and telecommunication in the long term is complementary, and increasing one increases the other. Since this study did not separate displacements based on their purpose and mode, these issues can be considered in future research. In addition, some other parameters comprising time, e.g., different times of the day or week, in creating the telecom and movement graph can help improve the result for urban planning. Furthermore, considering the users' demographic attributes such as age and gender in creating the graphs can yield results that can be used in location-based advertisement systems. Finally, even though the amount of data used in this study is acceptable for the period (about 1.5 years), the number of users is small compared to big data. Thus, using the data of more users can improve the results.

Literature and references:

Aderibigbe, O.-O. (2021). Are Telecommunications and Travel Substitutes or Complements? An Empirical Analysis of a Developing City in Nigeria. Findings, 30742. doi:https://doi.org/10.32866/001c.30742

Alessandretti, L., Lehmann, S., & Baronchelli, A. (2018). Understanding the interplay between social and spatial behaviour. EPJ Data Science, 7(1), 36. doi:https://doi.org/10.1140/epjds/s13688-018-0164-6

Andreev, P., Salomon, I., & Pliskin, N. (2010). State of teleactivities. Transportation Research Part C: Emerging Technologies, 18(1), 3-20. doi:https://doi.org/10.1016/j.trc.2009.04.017

Asgari, F., Gauthier, V., & Becker, M. (2013). A survey on human mobility and its applications. arXiv preprint arXiv:1307.0814. doi:https://doi.org/10.48550/arXiv.1307.0814

Barrat, A., Barthelemy, M., Pastor-Satorras, R., & Vespignani, A. (2004). The architecture of complex weighted networks. Proceedings of the National Academy of Sciences, 101(11), 3747-3752. doi:https://doi.org/10.1073/pnas.0400087101

Batty, M. (2013). The new science of cities: MIT press.

Baym, N. K., Zhang, Y. B., & Lin, M.-C. (2004). Social interactions across media: Interpersonal communication on the internet, telephone and face-to-face. New Media & Society, 6(3), 299-318. doi:https://doi.org/10.1177/1461444804041438

Becker, R., Cáceres, R., Hanson, K., Isaacman, S., Loh, J. M., Martonosi, M., Volinsky, C. (2013). Human mobility characterization from cellular network data. Communications of the ACM, 56(1), 74-82. doi:https://doi.org/10.1145/2398356.2398375

Cao, J., Li, Q., Tu, W., Gao, Q., Cao, R., & Zhong, C. (2021). Resolving urban mobility networks from individual travel graphs using massive-scale mobile phone tracking data. Cities, 110, 103077. doi:https://doi.org/10.1016/j.cities.2020.103077

Ceder, A. (2021). Urban mobility and public transport: Future perspectives and review. International Journal of Urban Sciences, 25(4), 455-479. doi:https://doi.org/10.1080/12265934.2020.1799846

Demissie, M. G., & Kattan, L. (2022). Estimation of truck origin-destination flows using GPS data. Transportation Research Part E: Logistics and Transportation Review, 159, 102621. doi:https://doi.org/10.1016/j.tre.2022.102621

Fan, H., Yang, B., Zipf, A., & Rousell, A. (2016). A polygon-based approach for matching OpenStreetMap road networks with regional transit authority data. International Journal of Geographical Information Science, 30(4), 748-764. doi:https://doi.org/10.1080/13658816.2015.1100732

Fan, H., Zipf, A., Fu, Q., & Neis, P. (2014). Quality assessment for building footprints data on OpenStreetMap. International Journal of Geographical Information Science, 28(4), 700-719. doi:https://doi.org/10.1080/13658816.2013.867495

Gao, S., Liu, Y., Wang, Y., & Ma, X. (2013). Discovering spatial interaction communities from mobile phone data. Transactions in GIS, 17(3), 463-481. doi:https://doi.org/10.1111/tgis.12042

Guo, D., Zhu, X., Jin, H., Gao, P., & Andris, C. (2012). Discovering spatial patterns in origin-destination mobility data. Transactions in GIS, 16(3), 411-429. doi:https://doi.org/10.1111/j.1467-9671.2012.01344.x

Hu, F., Li, Z., Yang, C., & Jiang, Y. (2019). A graph-based approach to detecting tourist movement patterns using social media data. Cartography and Geographic Information Science, 46(4), 368-382. doi:https://doi.org/10.1080/15230406.2018.1496036

Jamal, S., Habib, M. A., & Khan, N. A. (2017). Does the use of smartphone influence travel outcome? An investigation on the determinants of the impact of smartphone use on vehicle kilometres travelled. Transportation Research Procedia, 25, 2690-2704. doi:https://doi.org/10.1016/j.trpro.2017.05.201

Kim, M., & Cho, G.-H. (2021). Analysis on bike-share ridership for origin-destination pairs: Effects of public transit route characteristics and land-use patterns. Journal of Transport Geography, 93, 103047. doi:https://doi.org/10.1016/j.jtrangeo.2021.103047

Kong, H., Moody, J., & Zhao, J. (2020). ICT's impacts on ride-hailing use and individual travel. Transportation Research Part A: Policy and Practice, 141, 1-15. doi:https://doi.org/10.1016/j.tra.2020.08.012

Laurila, J. K., Gatica-Perez, D., Aad, I., Bornet, O., Do, T.-M.-T., Dousse, O., … Miettinen,

M. (2012). The mobile data challenge: Big data for mobile computing research. Paper presented at the Pervasive Computing.

Lim, H., Kim, S., & Heo, J. (2019). Graph analyses of phone-based origin-destination data for understanding urban human mobility in seoul, korea. Paper presented at the Proceedings of the 3rd ACM SIGSPATIAL International Workshop on Prediction of Human Mobility.

Mokhtarian. (1990). A typology of relationships between telecommunications and transportation. Transportation Research Part A: General, 24(3), 231-242. doi:https://doi.org/10.1016/0191-2607(90)90060-J

Mokhtarian, P., & Salomon, I. (2002). Emerging travel patterns: Do telecommunications make a difference? Paper presented at the Eighth Meeting of the International Association of Travel Behavior Research.

Monclar, R., Tecla, A., Oliveira, J., & de Souza, J. M. (2009). MEK: Using spatial–temporal information to improve social networks and knowledge dissemination. Information Sciences, 179(15), 2524-2537. doi:https://doi.org/10.1016/j.ins.2009.01.032

Montoliu, R., & Gatica-Perez, D. (2010). Discovering human places of interest from multimodal mobile phone data. Paper presented at the Proceedings of the 9th International Conference on Mobile and Ubiquitous Multimedia.

Nathan, R., Getz, W. M., Revilla, E., Holyoak, M., Kadmon, R., Saltz, D., & Smouse, P. E. (2008). A movement ecology paradigm for unifying organismal movement research. Proceedings of the National Academy of Sciences, 105(49), 19052-19059. doi:https://doi.org/10.1073/pnas.0800375105

Newman, M. E. (2008). The mathematics of networks. The new palgrave encyclopedia of economics, 2(2008), 1-12.

Opsahl, T., & Panzarasa, P. (2009). Clustering in weighted networks. Social networks, 31(2), 155-163. doi:https://doi.org/10.1016/j.socnet.2009.02.002

Saberi, M., Mahmassani, H. S., Brockmann, D., & Hosseini, A. (2017). A complex network perspective for characterizing urban travel demand patterns: graph theoretical analysis of large-scale origin–destination demand networks. Transportation, 44(6), 1383-1402. doi:https://doi.org/10.1007/s11116-016-9706-6

Senbil, M., & Kitamura, R. (2003). Simultaneous relationships between telecommunications and activities. Paper presented at the International Conference on Travel Behaviour Research.

Taylor, R. (1990). Interpretation of the correlation coefficient: a basic review. Journal of diagnostic medical sonography, 6(1), 35-39.

Toole, J. L., Herrera-Yaqüe, C., Schneider, C. M., & González, M. C. (2015). Coupling human mobility and social ties. Journal of The Royal Society Interface, 12(105), 20141128. doi:https://doi.org/10.1098/rsif.2014.1128

Turkle, S. (2012). Alone together: Why we expect more from technology and less from each other: Basic books.

van den Berg, P., Arentze, T., & Timmermans, H. (2013). A path analysis of social networks, telecommunication and social activity–travel patterns. Transportation Research Part C: Emerging Technologies, 26, 256-268. doi:https://doi.org/10.1016/j.trc.2012.10.002

Wang, J., Kwan, M.-P., & Chai, Y. (2018). An innovative context-based crystal-growth activity space method for environmental exposure assessment: A study using GIS and GPS trajectory data collected in Chicago. International journal of environmental research and public health, 15(4), 703. doi:https://doi.org/10.3390/ijerph15040703

Yuan, Y., Raubal, M., & Liu, Y. (2012). Correlating mobile phone usage and travel behavior–A case study of Harbin, China. Computers, Environment and Urban Systems, 36(2), 118-130. doi:https://doi.org/10.1016/j.compenvurbsys.2011.07.003

Zhang, S., Yang, Y., Zhen, F., Lobsang, T., & Li, Z. (2021). Understanding the travel behaviors and activity patterns of the vulnerable population using smart card data: An activity space-based approach. Journal of Transport Geography, 90, 102938. doi:https://doi.org/10.1016/j.jtrangeo.2020.102938

Esmaeili Tajabadi R., Pahlavani P., Hosseinpoor Milaghardan A. (2023). Graph-based Analysis of the Correlation between Mobility and Telecommunication, 67 (1), 40-57.
DOI: https://doi.org/10.15292/geodetski-vestnik.2023.01.40-57

Roya Esmaeili Tajabadi
Center of Excellence in Geomatics Eng. in Disaster Management, School of Surveying and Geospatial Eng., College of Eng., University of Tehran, Tehran, IRAN
e-mail: roya.esmaeili@ut.ac.ir

dr. Parham Pahlavani, Assoc. Prof.
Center of Excellence in Geomatics Eng. in Disaster Management, School of Surveying and Geospatial Eng., College of Eng., University of Tehran, Tehran, IRAN
e-mail: pahlavani@ut.ac.ir

dr. Amin Hosseinpoor Milaghardan, Assist,. Prof.
Department of Geographic Information Systems, Faculty of Civil and Surveying Eng., Graduate University of Advanced Technology, Kerman, IRAN
e-mail: amin_hoseinpoor@yahoo.com