Special issue article

Urban Analytics and City Science

EPB: Urban Analytics and City Science
2019, Vol. 46(7) 1362–1376

DOI: 10.1177/2399808319837982
journals.sagepub.com/home/epb
SAGE

Unveiling the inter-relations between the urban streets network and its dynamic traffic flows: Planning implication

Nimrod Serok
Tel Aviv University, Israel

Orr Levy and Shlomo Havlin
Bar-Ilan University, Israel

Efrat Blumenfeld-Lieberthal
Tel Aviv University, Israel

Abstract

Traffic flows have always been a major element affecting the nature of urban streets. Traffic flows influence the location of businesses, residences, and the development of real estate, land values, and built-density. In this study, we suggest that revealing the relations between the static street network and dynamic traffic flows may provide meaningful and useful insights that could be applied in planning processes. Thus, the objective of this work is to unveil the inter-relations between the dynamics of traffic flows and urban street networks in different areas of a city and between cities. We use network percolation analysis (i.e., removal of links with a speed value lower than a pre-defined threshold) to develop an innovative method to identify functional spatio-temporal street clusters that represent fluent traffic flow. We employed our method on two data sets of London and Tel Aviv centers and analyzed the dynamics of these clusters, based on their size (in terms of street length) and their spatial stability over time. Our findings revealed both the differences between the two cities as well as differences and similarities between different areas within each city. Thus, our method can be used to develop new, real-time, decision-making tools for urban and transportation planners. Today, new technologies provide big data on urban traffic flow, which can be used in developing new, adaptive tools for planning. However, urban and transportation planning are currently being challenged by real-time

Corresponding author:
Efrat Blumenfeld-Lieberthal, The Azrieli School of Architecture, The Yolanda and David Faculty of the Arts, Tel Aviv University, Ramat Aviv 69978, Israel.
Email: efratbl@post.tau.ac.il

navigation apps that aim to find the fastest routes for their users. To be able to intervene and affect urban life quality, planners should adopt new tools that are based on real-time, short-term approaches. These will bridge the gap between static long-term urban planning and the flexible and dynamic urban rhythm, and will enable planners to keep their role in the formation of better cities.

Keywords
Time–space analysis, traffic analysis, urban design, big data, Network theory

Introduction

The interdependencies between urban planning, and in particular land-use planning, and urban traffic have been widely discussed in the literature (Banister, 2005; Giuliano, 2004; Jiang, 2009; Manheim, 1979; Meurs, 2002; Wegener and Fürst, 2004). Traffic systems are being used for movement between different urban functions and locations, while land-use generates the map of origins and destinations for urban movement (Hillier, 1996, 2002). Human activities are mainly shaped by the underlying street network (Ma et al., 2019). On the other hand, human mobility within cities affects the level of exposure of different locations, which can be leveraged as a growth generator for businesses and alter land use. The circular causality between urban traffic and urban development is one of the most significant factors in current traffic planning. However, in order to achieve sustainable and efficient urban mobility patterns, the integration between urban and transportation planning must be improved (Banister, 2005; Cervero, 1998).

Traffic availability is a major factor in location decision-making of different land uses, and an important factor in the variations of real estate values. This hypothesis has been tested and proven widely (Fang et al., 2017; Ibeas et al. 2012; Mills, 1967; Von Thünen and Hall, 1966; Waddell et al., 2007). Today, there is extensive literature regarding the connection between the physical structure of the street network and the traffic movement on it (Bailenson et al., 2000; Crane, 2000; Hillier, 1996, 2002; Penn, 2003). However, this body of work refers to the urban system as static, while in reality, the traffic movement network is dynamic. This is true when referring to different time-scales such as hours during a day, different days of the week, and even different months of the year.

Traditionally, planners used transportation planning to influence the nature and the characteristics of different areas in the city. While high streets were characterized by wide roads and commerce/service land use, residential neighborhoods had been planned with side streets that were designed to hold the volume of transportation of their residents only. This was used as a route choice strategy by drivers who relied on a primary network for their navigation (Kuipers et al., 2003; Pailhous, 1984). New navigation apps (e.g., Waze, Google Directions) change the way people use urban roads as they are being directed to residential streets in order to avoid traffic congestion. These apps do not integrate considerations concerning public well-being or the quality of urban life in their algorithms and they are motivated only by their objective to minimize the duration of the journey. This changes the nature of neighborhoods and disturbs the life of their residents. Thus, the penetration of real-time navigation technologies has weakened the relationship between traffic and urban planning, as planners are no longer the leading influencers on the nature of traffic on urban streets. On the other hand, the increasing percentage of smartphone users is used to collect bottom-up data on their spatio-temporal movements. The result is the availability of big data on urban mobility, which can be used for studying usage in order to influence urban traffic. We argue that new planning perceptions should integrate real-time data and intervene in urban traffic flows not only in long-term plans but also in real-time interventions. By doing so, planners can join global trends to move to real-time decision-making methods and regain influence over the nature of urban streets and urban life.

Here, we developed a new framework that is based on complex network theory. This interdisciplinary field addresses, among others, spatially embedded transportation networks that control many aspects of modern urban life and thus affect problems such as traffic jams, urban sprawl, and epidemiology (Barthélemy, 2011). Many studies have focused on the influence of street network topology on traffic volumes (da Fontoura Costa, 2004; Freeman, 1977; Girvan and Newman, 2002; Grady et al., 2012; Serrano et al., 2009). Yet, recent work (Gao et al., 2013; Li et al., 2015) highlights the fact that most of the work on that subject has overlooked the dynamics of the traffic flow and the influence it has on the overall urban system.

A recent study (Li et al. 2015) has introduced an innovative approach that employs percolation processes in order to identify links that act as significant and repetitive temporal bottlenecks in urban traffic networks. The percolation process considers evolving relative velocities in streets segments, calculates the relative speed on each street segment at a given time (with respect to its maximum), and uses a speed threshold to define street clusters that represent functional modules, composed of connected roads with traffic speeds higher than the threshold. Li et al. (2015) defined the percolation speed threshold based on the maximum size of the second largest component, examined the resulting clusters, and then focused on the links that were identified as bottlenecks. This methodology, which has been tested on real urban data, not only reveals blocked links but also presents the resulting decomposing process of the city as spatio-temporal clusters that correspond to different traffic flows at different time scales (daily and weekly). This is based on a description of the city as a collection of local functional traffic-flow clusters connected by temporal bottlenecks.

Exploring the correlation between the dynamic percolation process of the traffic loads and the static street morphology may lead to meaningful insights and could be used in planning processes and be developed into new planning tools. Thus, the objective of this work is to unveil the inter-relations between the urban street network and the dynamics of traffic, in order to develop new, real-time, decision-making tools that can be used by planners.

We use network percolation analysis, which examines the robustness of the traffic flow-network to failure, to identify street clusters that represent functional modules, composed of connected roads with traffic load lower than a defined threshold. Unlike Li et al. (2015), we define a fixed speed threshold for the percolation process (as explained in the methodology section) and focus on the clusters themselves rather than on the links that connect different clusters. Based on the above, we identify spatially embedded clusters and track their dynamics at different temporal scales, ranging from hours to a week. By doing so, we present the different patterns of urban mobility, its evolution, and dynamics, and highlight areas and times that require the interventions of planners to improve urban life quality. Such interventions might include traditional planning tools, e.g., changing the land-use mixture; controlling the volumes of the built environment; formulating local business policies; planning public transportation systems; or even changing infrastructures. However, they should also include real-time prioritizing tools for adaptive and dynamic traffic light systems.

The rest of this paper is as follows: first, we present the methodology we developed to describe the dynamics of urban traffic flows and the data sets we used to test it. Then, we elaborate on the analysis tools we developed in order to evaluate different spatio-temporal processes. Finally, we present the results for our analysis and close with the discussion and the conclusions.

Methodology

We have developed an innovative methodology to follow the spatio-temporal dynamics of traffic flows. For this, we define two types of clusters: temporal clusters that represent the traffic flows at a given snapshot in time, and clusters that represent the change of the traffic flow over time. We analyzed the dynamics of the traffic flows and created spatially embedded, directed networks where the nodes represent intersections and the directed links represent road segments between two intersections (where motorized traffic is allowed in the examined direction). We followed Li et al. (2015) and calculated the 95th percentile of the maximal velocity measure on each link (street) during the day. Then, we set its temporal weight as the momentary relative speed with respect to its maximum value (Figure 1(a)). Different from Li et al., a link is defined as functional if its relative velocity (defined here as traffic "availability") is higher than 0.5 which, based on the canonic Greenshields equation (Greenshields et al., 1935), represents the maximum flow of vehicles (Figure 1(b)). We defined *clusters* as strongly connected components (using the Kosaraju algorithm; see Aho and Ullman, 1983) of streets with availability higher than 0.5 (e.g., a cluster is a collection of streets where one can drive from each point to all others without facing heavy traffic, i.e., relative speed <0.5).

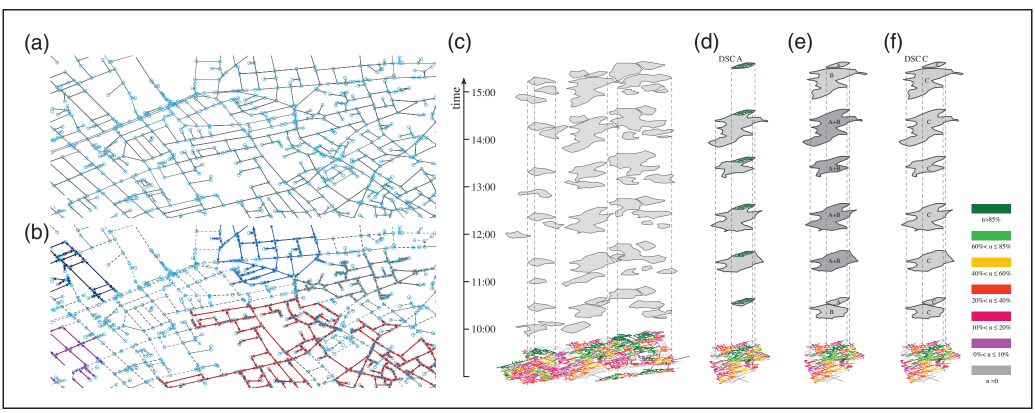

Figure 1. Defining the dynamic spatial clusters (DSC): (a) a directed network of urban streets, where nodes represent intersections and links represent street segments. The weight of the links is evolving and represents their traffic availability (relative velocity) at different times. (b) Snapshot example of London functional temporary clusters (FTC) where traffic availability (relative speed) ≥ 0.5, where different cluster colors represents different clusters. (c) A map of functional streets (with traffic speed ≥ 0.5) that represents the superposition of all the FTCs. In dark green: streets that are included in any of the FTCs in more than 70% of the samples (in this case—over 51 out of the 60 samples). (d) Dark green streets are the cores of potential DSC, i.e., a set of all overlapping FTCs that contained (at different times) the core streets.
(e) Different DSCs with significant overlapping of their streets (80–85%) are united into a single DSC, which is used for the analysis (f).

Clusters that crossed a minimum number of streets were defined as functional temporary clusters (FTC; Figure 1(c)). Due to the size differences between the cities, we set the minimum to 100 and 50 links for London and Tel Aviv, respectively.

Next, in order to follow the dynamics of the traffic flow in specific areas, we developed a method that integrates spatially overlapping FTCs into a newly developed type of spatio-temporal cluster that we called dynamic spatial clusters (DSCs). For this, we defined cores that represent spatial anchors for FTCs at different times. The core is defined based on the following stages: (1) we measure, for each link, the percentage of the time it was associated to any of the FTCs (online supplemental Figure S1), and (2) streets that appeared in 70% or more of the examined hours in an FTC are defined as anchor streets (Figure 1(d)). This threshold reflects (for the examined cities) anchor streets that represent different neighborhoods. Increasing this threshold will result in fewer DSCs that correspond to a lower number of cores, as we explain next. (3) A collection of connected anchor streets is defined as the core of a DSC. In the next stage, an FTC is assigned to a DSC if the core of the latter is included (partially or fully) in the former. Consequently, an FTC can be either assigned to a unique or to different DSCs and thus represent the spatial continuity or discontinuity of the traffic flow between the different cores at specific times. A set of FTCs that were assigned to one core defines a DSC. In other words, a DSC is a collection of FTCs with a mutual spatial anchor (Figure 1(e)). Finally, after all the DSCs are defined, we identified spatially overlapping DSCs and united them into a single one. In other words, merging the DSCs is a unification of their FTCs. This iterative process takes every pair of DSCs and analyzes their overlapping. This process can result in a spatial unification of the DSCs. The overlapping is based on the number of links in the smaller DSC and a pre-defined threshold. If the percentage of overlapping links crosses the threshold, the two DSCs are merged into one. The thresholds are based on the characteristics of the area and thus are unique for each city. We examined different values of this threshold for each city and chose the ones that yielded, on the one hand, a maximum number of DSCs and, on the other hand, merged spatially adjacent cores (that were originally located one street or two streets apart). Thus, the thresholds for London and Tel Aviv were set as 80% and 85%, correspondingly, which is also consistent with the findings of Gfeller et al. (2005). We continued this process until there were no more DSCs that could be merged (Figure 1(f)).

The above analysis has been performed for two time-frames: the first includes 24 hours for a seven-day week, and the second includes daytime only (12 hours between 08:00 and 19:00) for the five working days. The characteristics of traffic flow during night-time and weekends were found to be significantly different from its characteristics during the daytime on weekdays. During night-time, traffic availability, as expected, was considerably better and rather stable in comparison to daytime. The weekend, on the other hand, was characterized by less predictable traffic behavior in comparison to the weekdays. As we have collected data for only one weekend, we could not compare the behavior of the traffic flows at these days to the weekdays or to other weekends. Thus, in this work, we focus on the working day's data set and present only the results yielded from this data set.

The results of our analysis are presented for two cities: Tel Aviv and London. These cities represent different types of urban systems in terms of their size (the sampled area of the center of London is 2.5 times larger than the area of the center of Tel Aviv) and the transportation system within them. While London has an underground, overground, and national rail, in addition to a developed bus system, Tel Aviv has only a bus system and a national rail that operate within its center. Additionally, London has a congestion charge (a £11.50 daily charge) for driving a vehicle within the charging zones (that are included in the examined area) between 07:00 and 18:00, Monday to Friday. Tel Aviv, on the other hand, has no such restriction and vehicles move free of charge in the city center throughout the entire week.

We collected the velocities of 8850 road sections in London center and 2950 road sections in Tel Aviv center. The sampling frequency was 15 minutes over a week time (data for London were collected between the dates 21–27 March 2018 and the data for Tel Aviv center were collected between the dates 12–18 February 2017). We used interpolation to calculate the velocities of additional 9200 and 2450 road sections in London and Tel Aviv, correspondingly.

Analysis

To explore the spatio-temporal characteristics of the traffic flow, we based our analysis on different aspects of the DSCs. We start with the estimation of DSC traffic quality (TQ), continue with the probability of links to be included in the same DSC at different times, and conclude with the spatio-temporal stability of the DSC. These attributes were chosen as they provide a holistic picture of the dynamics of the traffic and highlight planning issues that need to be addressed (as will be demonstrated in the results section).

Traffic quality

We developed an index to evaluate the TQ and its dynamics, for different streets and areas. It is based on the assumption that good traffic is represented by a low number of FTCs that cover large areas, i.e., good traffic flow allows fluent mobility in large areas. Thus, the TQ is defined based on equation (1)

$$TQ = \sum_{1}^{n} \frac{\sum L_i}{R_i} \tag{1}$$

where n represents the number of FTCs at the examined time, $\sum L_i$ represents the sum of the lengths of the streets in an FTC ranked i, and R_i represents the rank of the FTCs, where $R_1 = 1$ indicates the largest area and $R_i = n$ the smallest area. Therefore, in the presented index, units are street lengths (KM) and higher values represent better TQ. The best TQ is achieved where there is only one FTC that covers the largest area of the surface.

The TQ of the DSCs has been analyzed based on the dynamics of the different DSCs at different times, as well as based on their rank-size distributions (see online supplemental Figure S1 for elaboration).

Area-stability: The probability of links to be included in a DSC at different times

In order to evaluate the DSC in terms of their spatial size as well as the stability of the links they hold at different times, we analyzed the descending cumulative distribution function (CDF) and its integral. The descending CDF shows the probability of any fraction of links to appear at least a certain fraction of the time in a DSC (see Figure 4). The integral of the CDF indicates, for each DSC, both the number of links it contained throughout the entire week as well as its stability. In other words, the integral of the descending CDF can be used to evaluate the quality of a DSC in terms of size (represented by the number of streets) and spatio-temporal stability (the appearance of the same links in the DSC at different times). Higher spatial-stability values represent a large and stable area, while lower values mean an unstable area or a stable but small area. The graph that holds the values of these integrals provides an overall perspective of the urban system and allows a comparison between different DSCs in a city and between different cities.

Stability

Note that the descending CDF does not separate the stability from the size of the DSC or indicate the stability at different hours. Thus, we developed an index that offers an indication regarding the level of spatio-temporal stability for each DSC and at a given window of each measured time.

We followed the dynamics of the spatial structure of the DSCs over time and calculated their spatial stability for each hour during weekdays only. This is based on the previous findings that indicate significant differences between weekdays and weekend in terms of traffic flow. The spatial stability (S) is calculated based on equation (2)

$$S = \frac{\sum_1^m l_{FTC}}{m * L_{DSC}} \tag{2}$$

where l_{FTC} represents the number of links (street segments) in each of the FTCs included in the examined DSC at a specific hour, and L_{DSC} represents the total number of links that appeared at least once in the examined DSC at that hour. m represents the number of days used for the calculation, which is 5 in our case. $S = 1$ is at its maximum when $\sum_1^m l_{FTC} = m * L_{DSC}$. This indicates that all the FTCs are spatially identical in all the examined days at a specific hour. When $\sum_1^m l_{FTC} = L_{DSC}$, none of the links appears more than once in the DSC, and its stability is at its minimum. For our calculation (based on 5 working days), this minimum = 0.2; the results were normalized to a range between 0 and 1. Unlike other methods (e.g., the Jaccard index), our method characterizes, in one simple number, not only the overlapping that occurs in all the examined samples (days) but also takes into account overlapping that occurs between some of the days. By using this method, we can follow the temporal stability of the spatial behavior of the traffic flows.

Results

We used the traffic flow averages of each road segment to identify the cores of the DSCs and found 20 DSCs for London and 9 for Tel Aviv (online supplemental Figure S2a). The DSCs in the two cities present different characteristics in terms of the dynamics of their stability and TQ. While some of the variances between the cities could be explained by their different scales, others are related to other differences between the cities (e.g., the characteristics of the DSCs).

The TQ is an indicator for the physical area of the DSCs, which represents the area with good traffic flow, where high values of TQ correspond to large area coverage (good traffic flow) of the DSC. We use the standard deviation (σ) of the TQ values of the DSCs to present the variation of their area coverage. Low σ corresponds to steady area coverage at different times while high σ indicates large variation in the TQ.

While the σ values of the TQ in Tel Aviv are similar for all the DSCs, in London they increase for DSCs with high TQ (Figure 3(a) and (b)). This means that the TQ of the DSCs in Tel Aviv is varying similarly (and significantly) for all sizes. In London, on the other hand, DSCs that cover small areas are more likely to remain small throughout different times, and DSCs that cover large areas are more likely to change their size at different hours and days. These values highlight steady and local DSCs in Tel Aviv and more global and unstable ones in London. Thus, they can be used as a decision-making tool for planners, since they provide overall insight into the spatial dynamics of the DSC. In addition, this tool identifies neighborhoods that are well connected to the rest of the city and others that are constrained in terms of their traffic flow. This also suggests that the dynamics of the DSCs do not follow a universal law and are location dependent. This strengthens the need to integrate bottom-up data that emerges from the local setting in planning processes.

The dynamics of the TQ over time (Figure 3(c) and (d)) reveals that the maximum TQ values of the different DSCs ranged from 6365 to 83,185 meters in London and from 26,320 to 112,790 meters in Tel Aviv. The two cities show a major difference in the dynamics of their TQ: in London, the high TQ occurs in the early morning (08:00) or late afternoon (after 17:00) while in Tel Aviv, high values of TQ occur at different hours on different days. This suggests that the dynamics of traffic flow patterns in Tel Aviv are less predictable than those in London.

The TQ of most of the DSCs in London reaches very high peaks in distinct hours (see some examples in Figure 3(c)). An example of this behavior is found in the SoHo DSC. In most hours, it is limited to the western part of SoHo (Figure S2a) and has very low values of TQ. However, in the mornings (every day at 08:00), it is connected to most of the other neighborhoods in the north bank of the River Thames and twice, after 17:00, it was connected to Mayfair, Marylebone, and Covent Garden. The Finsbury & Islington DSC (Figure 2(a)) is an example of a different type of behavior. The core of the latter is not constrained to one neighborhood and it crosses two nearby ones (Finsbury and Islington). In more than 40% of the time, the streets included in it covered most of Shoreditch, Hoxton, Clerkenwell, and the eastern part of Barbican. During the rest of the time, it spans to the surrounding areas of these neighborhoods and once (on Monday at 17:00), it covered most of the streets on the north bank of the River Thames. At that time, most of the DSCs presented significantly high values of TQ, but unfortunately, we could not find any event that might have caused this irregularity.

In Tel Aviv, on the other hand, the change in the TQ of the DSCs is more moderate and smooth as the TQ of the DSCs varies and reaches high values many times at different hours; see Figure 3(d). We assume this is because the traffic-flow in Tel Aviv is not constrained by neighborhoods and thus more regional. The Bavli-Bney-Dan DSC (Figure 2(c)) is a good example of this, as its core spans from the northeast to the northwest neighborhoods of Tel Aviv. In more than 40% of the time, it covered parts of four different neighborhoods in the northern part of the city and at the rest of the time it covered most of the examined area. This DSC is better described as the northern region of the examined area rather than just by its core (online supplemental Figure S3).

An exception is Shikun HaKtsinim, which presents low TQ values most of the time, with several peaks at a few different times; see Figure 3(d). This cannot be explained only by its size, as Kerem HaTeymanim (Figure 2(d)) is similar to it in terms of the number of links they hold (Figure 4). An explanation for this might be found in its unique morphology: this clustered area is connected to the rest of the city only 10% of the time, and during the rest of the hours, it covers a small area and presents very low values of TQ.

Figure 4(a) and (c) presents some examples of the CDF of different DSCs in London (a) and Tel Aviv (c). The curve of each DSC provides meaningful insights about its characteristics in terms of size and stability. Holborn and Marylebone DSCs, for example, cover, at their maximum size, 50% and 37% of the measured area, respectively. However, the CDF of Holborn DSC decreases faster than that of Marylebone DSC. Thus, in 90% of the samples, Marylebone DSC includes significantly more streets than Holborn DSC. In other words,

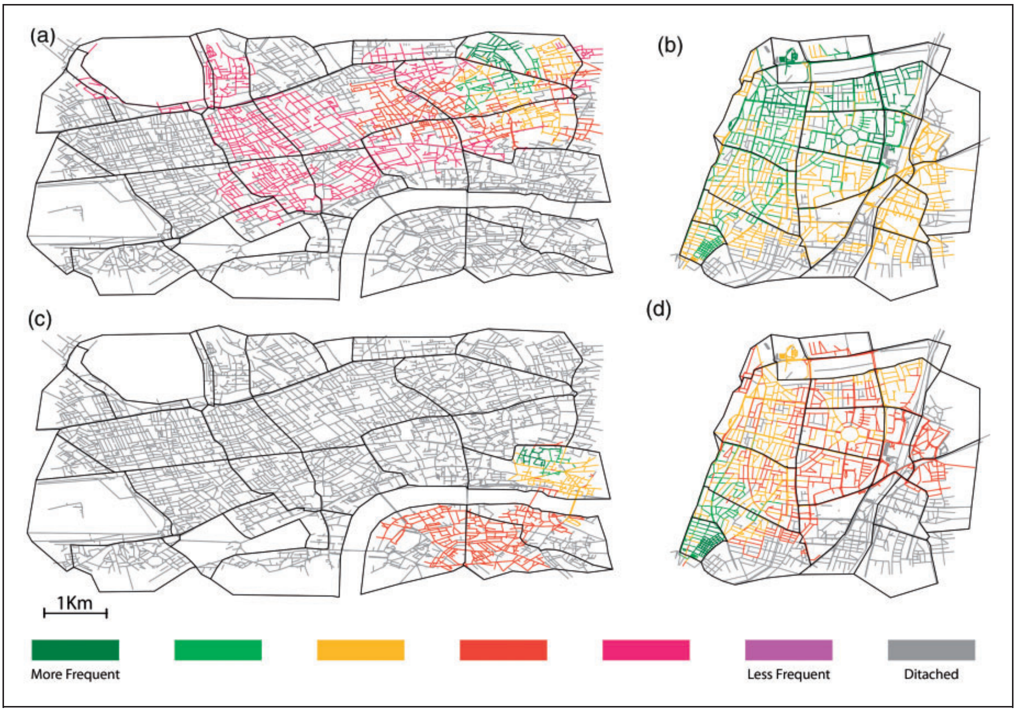

Figure 2. Examples of DSCs in London and Tel Aviv. For this analysis we used Head–tail classification (Jiang, 2013; Jiang and Yin, 2014) to visualize the heavy-tailed distribution properties of the data (see online supplemental Figure S1 for elaboration). The colors represent the frequency of each link included in the DSC in the entire studied period (12 hours over 5 weekdays): (a) Finsbury & Islington, London, (b) The City of London, (c) Bavli-Bney Dan, Tel Aviv, and (d) Kerem HaTeymanim, Tel Aviv.

Marylebone DSC has better traffic flow as it includes more repeating streets. Southwark–London Bridge DSC is a small but stable one: a fixed number of streets (that represents its core) appear in more than 90% of its samples. This number is higher than the number of streets that appeared repeatedly in Holborn DSC (and represent its core) 40% of the time. Figure 4(b) and (d) presents the values of the integrals of each of the DSC curves, multiplied by the total number of the measured streets. Thus, the area-stability values are represented by the total number of links that were associated to a DSC at all times, and the probability distributions of links to appear in it at different fractions of times. This index highlights the differences between the two cities: while most of the DSCs in Tel Aviv present similar characteristics in terms of their size and stability, London DSCs can be divided into three groups: DSCs with high, average, or low values of size and stability. The DSCs in the first group are similar to the DSCs in Tel Aviv as they span beyond one neighborhood on a regular basis. The DSCs in the second group occupy the area of one neighborhood most of the time (40% or more), and the ones in the last group mostly occupy only parts of a single neighborhood. The two DSCs with the lowest values, Knightsbridge and Belgravia, are a good example of the strength of the present tool. The area defined in this study does not cover these entire neighborhoods but splits them in the middle. The result is a somewhat broken traffic-flow patterns, which are revealed in the low values presented in Figure 4. On the other hand, DSCs, such as the City of London (the historic business district, presented in Figure 2(b)) or others in the South Bank, present low values of area-stability due to

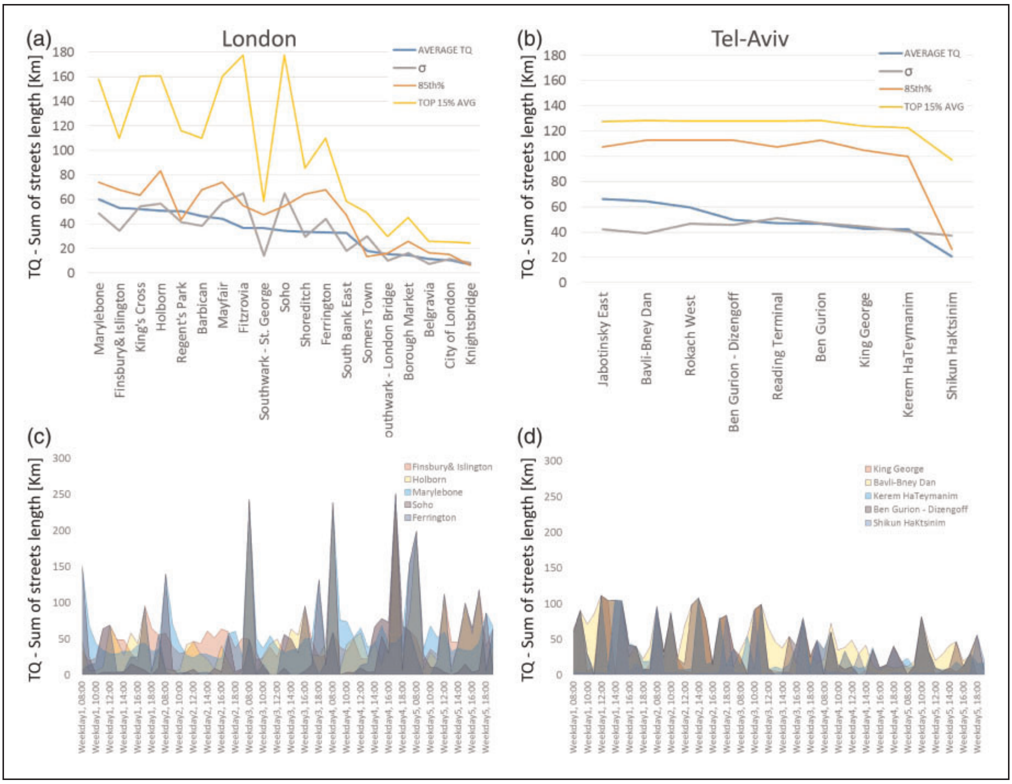

Figure 3. Average and maximal traffic quality (TQ) values and standard deviation (σ) for DSCs in London (a) and Tel Aviv (b). The maximum values refer to maximum values that appeared at the 85th percentile of the samples and the average of the top 15% of values. The dynamics of the Traffic Quality of five typical DSCs in (c) London, and (d) Tel Aviv.

their area coverage, which covers the entire neighborhood only less than 20% of the time. During the rest of the time, the DSC covers only part of the neighborhood. In this, the City of London is very different from Barbican—its adjacent neighborhood. The DSC with its core in the Barbican area spans north to Clerkenwell and Islington more than 40% of the time. Both neighborhoods (City of London and Barbican) are parts of the business district of London, but while the first is constrained in terms of traffic flow, the second is better connected to its surroundings. For planners, this information can be used in order to prioritize different planning decisions. Another example is the DSCs in the South Bank. In this small area, there are four different DSCs with their cores located in proximity to each other (online supplemental Figure S2a). The area includes two major neighborhoods, South Bank and Southwark, where the latter has three different DSCs within its boundaries. These DSCs present low area-stability values, which imply to planners that traffic flow in this area needs improvements.

From the stability index and the values of its DSCs in London and Tel Aviv, we can also see significant differences (Table 1). The average stability for the DSCs in London is 0.41 ± 0.21 in comparison to 0.19 ± 0.12 in Tel Aviv. The stability values of the DSCs in London range from 0 to 0.96 and half of them present average stability values ≥ 0.4.

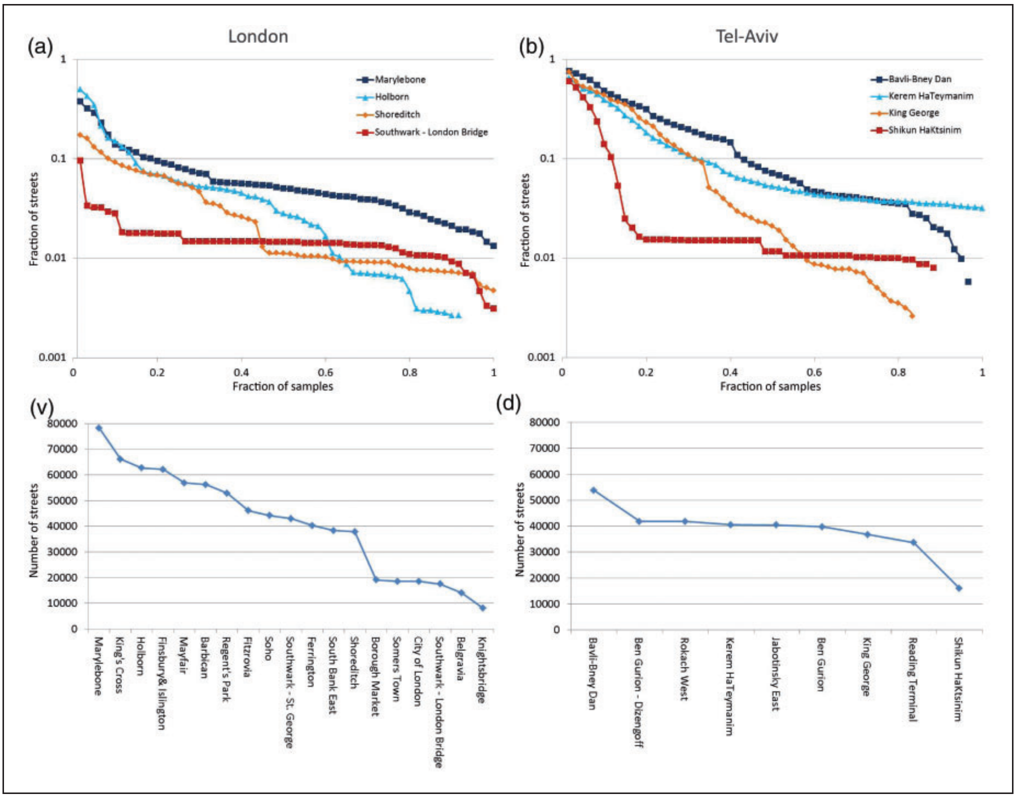

Figure 4. The probabilities of links (streets) to be included repeatedly in different DSCs (a) London, (c) Tel Aviv; and the area-stability values of the DSCs, calculated as the integral of the CDF presented in (a) and (c) multiplied by the number of measured streets (b) London, (d) Tel Aviv.

High stability values (0.6 and higher) are observed for different DSCs at different hours throughout the examined period. Thus, generally speaking, it can be said that most of the DSCs in London are stable in terms of their spatial dynamics. Unlike the area-stability values, the stability index presents the stability of the DSCs at specific hours while the area-stability values refer to the spatio-temporal stability of the DSCs throughout the entire week. Thus, five DSCs such as Holborn, Soho, Shoreditch, Ferrington, and Fitzrovia present average to high area-stability values (Figure 4) but their stability index values are low. Looking at the other end of the scale, the DSCs in the South Bank have low area-stability values and high stability index values. The explanation of these examples is rooted in the fact that the stability-area values consider both factors while the stability index concerns the stability of DSCs regardless of their size. Each of these analyses provides different insights regarding the overall traffic flow quality of the DSCs as well as the entire city. They are needed in order to answer different questions, e.g., while the area-stability values can be used to prioritize planning and regulation, the stability index can be used for local modifications in tube/bus frequencies or traffic-light operation.

In Tel Aviv, on the other hand, most of the DSCs show low stability values that range between 0 and 0.35 with a few exceptions that are related to two DSCs: Shikun HaKtsinim and Kerem HaTeymanim. These DSCs have the lowest average

Table 1. Stability values, S (equation (2)), for the DSCs in London and Tel Aviv at different hours.

London	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	Average
Somers Town	0.05	0.9	0.52	0.88	0.88	0.87	0.85	0.45	0.9	0.88	0.16	0.96	0.69
Southwark–London Bridge	0.56	0.46	0.65	0.76	0.82	0.67	0.61	0.95	0.46	0.16	0.39	0.9	0.62
Regent's Park	0.12	0.67	0.77	0.82	0.82	0.72	0.79	0.65	0.8	0.11	0.27	0.2	0.56
Belgravia	0.68	0.57	0.77	0.5	0.3	0.5	0.55	0.67	0.45	0.65	0.68	0.4	0.56
Knightsbridge	0.68	0.48	0.84	0.69	0.24	0.84	0.23	0.24	0.46	0.68	0.48	0.73	0.55
Marylebone	0.53	0.6	0.5	0.57	0.45	0.6	0.64	0.43	0.54	0.51	0.35	0.28	0.50
Southwark–St. George	0.52	0.45	0.5	0.48	0.48	0.49	0.66	0.52	0.58	0.4	0.4	0.29	0.48
South Bank East	0.44	0.15	0.47	0.33	0.37	0.52	0.62	0.54	0.58	0.36	0.32	0.24	0.41
Borough Market	0.52	0.25	0.61	0.41	0.64	0.51	0.52	0.57	0.31	0.16	0.19	0.18	0.41
City of London	0.44	0.29	0.25	0.42	0.53	0.28	0.41	0.51	0.43	0.42	0.61	0.17	0.40
Finsbury & Islington	0.52	0.3	0.32	0.43	0.29	0.43	0.56	0.36	0.27	0.25	0.42	0.46	0.38
King's Cross	0.35	0.62	0.45	0.39	0.23	0.48	0.39	0.35	0.34	0.23	0.29	0.42	0.38
Barbican	0.5	0.24	0.47	0.34	0.22	0.39	0.55	0.33	0.3	0.23	0.29	0.46	0.36
Mayfair	0.5	0.43	0.28	0.41	0.27	0.23	0.58	0.2	0.51	0.54	0.19	0.1	0.35
Holborn	0.34	0.6	0.35	0.31	0.34	0.17	0.31	0.13	0.33	0.2	0.17	0.37	0.30
Soho	0.53	0.29	0.14	0.34	0.42	0.22	0.47	0.16	0.18	0.04	0.14	0.07	0.25
Shoreditch	0.34	0.2	0.24	0.15	0.09	0.22	0.2	0.29	0.23	0.32	0.36	0.22	0.24
Ferrington	0.3	0	0.2	0.09	0.15	0.13	0.39	0.29	0.21	0.18	0.05	0.34	0.19
Fitzrovia	0.53	0.31	0.23	0.16	0.25	0	0	0.17	0.13	0.06	0.19	0.07	0.18
Tel Aviv	8:00	9:00	10:00	11:00	12:00	13:00	14:00	15:00	16:00	17:00	18:00	19:00	Average
Kerem HaTeymanim	0.23	0.31	0.24	0.17	0.12	0.63	0.19	0.2	0.3	0.31	0.41	0.32	0.29
Bavli-Bney Dan	0.2	0.32	0.28	0.25	0.26	0.29	0.3	0.33	0.21	0.24	0.26	0.25	0.27
Shikun HaKtsinim	0.04	0.62	0.05	0.58	0.69	0.09	0.03	0.03	0.34	0.05	0.14	0.09	0.23
Rokach West	0.07	0.14	0.18	0.24	0.23	0.22	0.21	0.32	0.21	0.19	0.2	0.03	0.19
Ben Gurion–Dizengoff	0.14	0.16	0.28	0.1	0.06	0.14	0.14	0.33	0.19	0.27	0.14	0.15	0.18
Jabotinsky East	0.09	0.19	0.27	0.16	0.18	0.29	0.24	0.23	0.04	0.09	0.16	0.04	0.17
Ben Gurion	0.18	0.12	0.26	0.13	0.06	0.13	0.15	0.23	0.19	0.27	0.07	0.07	0.16
King George	0.18	0.2	0.23	0.16	0.03	0.03	0.03	0.17	0.19	0.27	0.07	0.14	0.14
Reading Terminal	0.07	0.03	0.03	0.13	0.17	0.22	0.21	0.25	0.2	0.2	0.1	0.06	0.14

Red represents the lowest values and green represents the highest values.

TQ (Figure 3) and cover mainly the immediate surroundings of their cores, which are characterized by unique morphologies. Shikun HaKtsinim contains a few parallel dead-end streets that are connected to a perpendicular street, which connects them to the rest of the city. Kerem HaTeymanim, which is one of the oldest neighborhoods of Tel Aviv, is typified by a dense, orthogonal grid of one-way streets. Thus, it can be assumed that the high stability index of these DSCs results from the constraints their morphology imposes on their intra- and inter-traffic.

To summarize, the spatial behavior of the traffic flow in London is more stable (thus predictable) than that of Tel Aviv in terms of hourly behavior. Tel Aviv, on the other hand, presents a more stable overall behavior in terms of the similarity between the area-stability values of its DSCs. We assume that this is due to the fact that the traffic flow in London is, generally speaking, constrained most of the time to local neighborhoods, while the traffic flow in Tel Aviv is more regional than local. Tel Aviv is a relatively new city, built on a North-South and West-East road network, which can explain the regional traffic flow within it. London, having developed organically for centuries, has a more obvious neighborhood structure and the intra-traffic flow (within the neighborhoods) is different from the inter-traffic flow between different parts of the city.

Summary

We have based our work on the perception that was introduced by Hägerstrand (1970) and has been widely tested since, that the city is a dynamic entity in term of its spatio-temporal behavior. We developed an innovative method for the identification of functional dynamic areas in the city in terms of their traffic flow. Our method is based on two types of spatio-temporal clusters: the first is the FTC, which represents temporal functional clusters and contains connected streets that crossed an availability threshold of 0.5. They exist at specific times and evolve with time. The second type is the DSC, which integrates spatially overlapping FTCs into one cluster that represents the change in traffic flows in a specific area over time. We employed our methods on two data sets for London and for Tel Aviv centers and analyzed the dynamics of the DSCs based on their spatial size (measured as the sum of the street length), and their spatio-temporal stability. Our findings revealed both the differences between the two cities as well as differences and similarities within each city.

We demonstrated how the DSC analysis could be used as a comparative tool to study the spatio-temporal behavior of different cities as well as different areas within a city. The DSC enables identification (both in real-time and over time) of the boundaries of functional areas in the city. This can be useful for developing decision-making support tools for urban planners in their long-term planning processes (e.g., land-use distribution, infrastructure development and alternation, public transportation routes, etc.) as well as in real-time (e.g., adaptive traffic light systems, and public transportation frequencies). Additionally, revealing the dynamics boundaries of the DSCs is significant for planners as these boundaries (and the area they hold) affect pedestrians, bike riders, businesses and more.

"The relation between micro-economic activity and space, like the relation between culture and space, is largely mediated by movement." (Hillier, 2002)

Urban and transportation planning are currently being challenged by real-time navigation apps that aim to find the fastest route for their users. The companies that operate these apps are motivated by their goal to minimize travel time and do not integrate considerations regarding urban life quality, or public well-being in their algorithms. In order to be able to intervene and affect the nature of different urban areas, planners must adopt new tools that are based on real-time, short-term approaches. These will bridge the gap between static long-term urban planning and the flexible and dynamic urban rhythm, and enable planners to keep their role in the formation of better cities.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the PMO Foundation for Innovations in Transportation.

Supplemental material

Supplemental material for this article is available online.

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Nimrod Serok is a PhD candidate at the Azrieli School of Architecture at Tel Aviv University, where he also completed his BArch and MA (both first in his class). His work focuses on urban complexity with an emphasis on urban mobility patterns and spatio-temporal data analysis. He is experienced as a practicing architect and urban planner. Nimrod works as a spatial-optimization algorithms developer, dealing with real-life urban mobility challenges, aiming to make city travel simpler.

Orr Levy (Postdoctoral student) is a Researcher in the Physics department at Bar-Ilan University, under the supervision of Prof. Shlomo Havlin. He received his MSc from the Biomedical Engineering department at the Technion, under the supervision of Prof. Isak Gath and his PhD in the Physics department at Bar-Ilan University, under the supervision of Prof. Shlomo Havlin. His main research interest is the study of complex systems using approaches from complex networks science. Specifically, he is interested in studying Traffic networks, Social networks, and Biological networks. Two of his publications were recently published in PNAS and Science Advances.

Shlomo Havlin (PI) is a Professor of Physics at Bar-Ilan University and the 2018 Israel Prize recipient in the field of Physics. He is a leading expert and pioneered many aspects of theoretical network analysis. Havlin has 40 years of experience in training and research. He won the Rothschild Prize in Physics, Israel (2014), the Lilienfeld Prize for "a most outstanding contribution to physics", APS, USA (2010), and the Weizmann Prize for Exact Sciences, Israel (2009). Prof. Havlin is the author of more than 700 articles with many publications in prestigious scientific journals. He is author and editor of 11 books.

Efrat Blumenfeld-Lieberthal is the Head of the David Azrieli School of Architecture at the Tel Aviv University (TAU) since October 2018, and a member of the founding team and steering committee of City Center-TAU Research Center for Cities and Urbanism. She received her BArch, MA, and PhD at the Faculty of Architecture and Town Planning, at the Technion IIT. Her research interests are applying theories of complexity to urban environments; urban morphology; size distribution of entities in complex systems; complex networks in urban and human systems, and smart cities and the way they influence urban development.