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On the variability of human activity spaces
contribution to "The real and virtual world of planning"

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Contribution to “The Real and Virtual World of Planning”

On the variability of human activity spaces

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Abstract

Humans are territorial in their repeated use of a very small subset of the possible number of activity locations. While these activity spaces have been measured extensively for animals, there is virtually no literature on the size and structure of human activity spaces, or rather the existing literature is severely limited by its insufficient databases. A recent data collection effort, a six-week travel diary in Karlsruhe and Halle (Mobidrive), allows for the first time to derive credible measures of the size and structure of human activity spaces for individuals.

This chapter first develops a series of measures of these spaces, starting from the simple (adaptations of the Jennrich-Turner home range) and moving to the complex (buffered minimum spanning networks). The second part of the chapter reports the distribution of the sizes of these measures and analyses the sociodemographic and situational determinants of their size. The conclusions develop the further research agenda and highlight the consequences of these results for the modeling of human behavior in transport and spatial planning.

Keywords

Activity space – development of measures – longitudinal travel data – Mobidrive – ETH Zurich – Institute for Transport Planning and Systems (IVT)

Preferred citation style

1 REPRESENTING AND MEASURING LOCATIONAL CHOICE AND HUMAN MOVEMENT

The day-to-day perspective of individual travel behaviour (i.e. *intra-personal variability*) has been the foci of a range of transport research studies during the last 40 years. Subject of numerous was for example the stability and flexibility in personal travel (Herz, 1983), variability (Hanson and Huff, 1982, 1988a, 1988b; Pas, 1986 and 1987), rhythms (Huff and Hanson, 1990) or the dynamic adjustment of behaviour towards a changing travel environment (Mahmassani, Hatcher and Caplice, 1997; Mannering and Hamed, 1990).

Another important aspect of daily mobility is the usage of space constituted by the locational choice of the travellers. The acquisition as well as the perception of the urban environment and the actual navigation through nets is captured by the micro-geographical *activity space concept* which will be developed in this paper through new methods.

The activity space idea – which was developed in parallel with a range of related approaches to describe individual perception, knowledge and actual usage of space in the 1960s and 1970s (see Golledge and Stimson, 1997 for a discussion) – aims to represent the space which contains the places frequented by an individual over a period of time. Activity spaces are (geometric) indicators of the *observed or realised* daily travel patterns (see also Axhausen, 2002). This is stressed here as related concepts such as the *action space* (e.g. Horton and Reynolds, 1971), the *awareness space* (e.g. Brown and Moore, 1970), the *perceptual space* (e.g. Dürr, 1979), *mental maps* (e.g. Lynch, 1984) or *space-time prisms* (e.g. Lenntorp, 1976) describe the individual potentials of travel – based on spatial knowledge, mobility resources, the objective supply of opportunities etc. An activity space is here defined as a two-dimensional form which is constituted by the spatial distribution of those locations a traveller has personal experience (*contact*) with. Figure 1 gives an schematic representation of activity spaces with each dot representing a unique activity location visited over a six-weeks survey period and the lines indicating the observed links between those locations.
In activity spaces, travellers choose routes through time and space to meet their obligations, needs and desires. The travellers will try to choose these routes optimally, but they are constraint by their knowledge (mental map), their reasoning abilities and by the time and concentration they have available to construct and select a route. In a wider sense, the activity space comprises both those locations of which a traveller has personal experience, as well as those of which the traveller has second hand experiences through family, friends, books, films or other media (the knowledge space) (see e.g. Horton and Reynolds, 1971; Dürr 1979 or Goldenberg, Libai and Muller, 2001). In the following, though, activity space refers only to the first set of locations, those which a traveller has personally visited.

While the concept of activity space has been put forward for about four decades, most empirical work has focussed on the structures of the mental mapping of locations (see e.g. Lynch, 1960 or Downs and Stea, 1977). Where empirical work has been done on a geometrical representation of personal activity spaces or even the measurement of their sizes, the focus was mostly on travel potentials or opportunities. Geometrical representations like ellipses were often used to visualise binding constraints or better opportunities to travel e.g. by advanced technology (see Saxena and Mohtarian, 1997). This was often inspired by the conceptual approaches of space-time geography which puts spatial movement into a context of individual and societal and constraints (Hägerstrand, 1974; Chapin, 1974). Only few studies concen-
trated on the detailed measurement of individual activity spaces (Dijst and Vidaković, 1997; Dijst, 1999).

The main reason why the physical mapping or enumeration of the places visited by individuals has been only rudimentary so far is the lack of long-term travel behaviour data. Such data would provide a comprehensive list of visited locations with detailed attributes and information about the relationship between the places. As researchers already stated in the early 1980s, activity space research suffers the deficit that it is almost entirely led by hypotheses on longitudinal travel behaviour which can be tested only on aggregate data based on cross-sectional observations (Dangschat, Droth, Friedrichs, Heuwinkel and Kiehl, 1980). Hence, travel behaviour research as well as transport policy and planning have to rely on the knowledge about mobility patterns observed on single days which are interpreted as long-term optimal decisions and as a state of behavioural equilibrium.

The recent availability of the multi-week Mobidrive travel data makes it now feasible to measure the extent of individual activity spaces and to test hypotheses about the usage of urban space and the multi-centred structure of our daily mobility (see Axhausen, Zimmermann, Schönfelder, Rindsfüser and Haupt, 2002 for details of the study). The analysis of the Mobidrive data allows to reveal the spatial characteristics of our daily activity repertoire and therefore an important pillar of our personal world which consists of realised behaviour, mental maps and expectations towards not yet visited areas. By analysing the spatial manifestation of our daily life activity needs and preferences such as represented in Figure 1, this will help us to improve our forecasts on locational choice and the interaction between urban space, sociodemographic and travel behaviour (Kutter, 1980).

This paper presents approaches to represent and quantify individual activity spaces based on the Mobidrive survey. To our knowledge, this study is the first to analyse human activity spaces based on individual panel data.

The remainder of the paper is organised as follows: First, the long-term Mobidrive data set is introduced. The third chapter presents new methodological approaches to represent and to measure individual activity spaces using (spatial) statistical methods. This is followed by a comparison of the developed approaches. Finally, the conceptual work and the related estimation results are evaluated from an analytical and from a planning point of view.

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1 It should be noted that there is a range of studies of spatial behaviour and activity spaces on the aggregate level of sociodemographic groups or zones (see e.g. Kutter, 1973; Zahavi, 1979; Beckmann, Golob and Zahavi, 1983a, b; Holzapfel, 1980; Scheiner, 2001). Those studies use cross-sectional travel or time-use data.
2 THE MOBIDRIVE TRAVEL DATA SET: SURVEY DETAILS AND ADDRESS GEOCODING

The collection and the exploration of longitudinal travel behaviour data was addressed in the German research project Mobidrive in 1999. Whereas transportation research has so far mainly focused on the cross-sectional analysis of persons’ and households’ mobility patterns, Mobidrive was designed to obtain a more detailed picture of long-term mobility (Axhausen et al., 2002). The underlying motive for the ambitious data collection which exceeds the usual observation period of one day by several weeks, was the realisation that “(t)he single constant about travel behaviour is that it is constantly changing” (Long, 1997, xv). The data collection procedure was followed by an extensive analysis of the travel data and the parallel development of methodological approaches to capture behavioural variability (see Zimmermann, Axhausen, Beckmann, Düsterwald, Fraschini, Haupt, König, Kübel, Rindsfüser, Schlich, Schönfelder, Simma and Wehmeier, 2001; Axhausen et al., 2002).

Survey description

The Mobidrive project conducted a panel survey in which the respondents travel behaviour was observed for a 42 days. Based on experiences made with a similar survey in the 1970s (Uppsala Household Travel Survey, see e.g. Marble, Hanson and Hanson, 1972), the continuous six-week travel diary survey was conducted in the German cities of Halle/Saale and Karlsruhe in autumn 1999. A total of 317 persons over 6 years in 139 households participated in the main phase of the survey, after testing the survey instruments in a pre-test with a smaller sample in spring 1999 (44 persons). The paper-based travel-diary instrument was supplemented by further survey elements covering the socio-demographic characteristics of the households and their members, the details of the households’ car fleet and transit season tickets owned and personal values as wells as attitudes towards the different modes of transport. The Mobidrive data finally offers a unique level of detail for travel diary surveys of that type (see Axhausen et al., 2002 for details of the survey characteristics).

Address geocoding

One objective of the Mobidrive consortium was to provide exact locational data in order to facilitate the analysis of the variability in spatial behaviour over time. One relevant analysis

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2 See also http://www.ptv.de/mobidrive
direction is the estimation of destination-, route- and mode-choice models which is dependent on the accurate generation of shortest origin-destination paths (see e.g. König and Axhausen, 2001; Cirillo and Axhausen, 2002).

The precise locational data was obtained by geocoding the trip destination addresses of all main study trips (approximately 40,000 trips). The addresses – including home and workplace locations – were transformed into Gauss-Krüger coordinates in a WGS 84 (World Geodetic System) geodetic reference system. The geocoding was positive for about 95% of the reported trips.

Due to incomplete addresses and limited availability of digital address information outside the urban cores of the case study regions, the geocodes of the addresses have different degrees of resolution for the different spatial units. For the municipalities City of Karlsruhe and City of Halle, the street addresses could be geocoded on the basis of (small) building blocks (i.e. more than 90% of all geocoded trips), whereas outside the urban boundaries the addresses are available as geocodes of the centroids of the municipality, only. This has of course implications for any spatial analysis as the geocoding does not yield a 100%-exactness for the locational data – especially for non-local trips. The number of unique locations can be assumed to be slightly higher than what is revealed by the geocodes. Furthermore, the fact that trip destinations outside the city boundaries are aggregated to one single x-y-coordinate restricts the interpretation spatial analysis results. Exact results can be only expected for the local part of the overall mobility. As most of the ongoing investigations are of a comparative character, though, this lack of precision can be accepted.

In addition to the georeferenced trip data, there is selected digital land use information available for both case study cities. This allows to combine travel demand and supply data for the behavioural analysis. A detailed road network is available only for Karlsruhe.
3 MEASURING ACTIVITY SPACES: A CONCEPTUALISATION OF APPROACHES

The lack of previous empirical research in human activity spaces requires the development of suitable new measures to capture the activity spaces revealed in the Mobidrive panel. Such new indicators should describe cover both, the qualitative i.e. graphic character to visualise travellers’ movements in their urban environment and quantitative features to estimate and compare spatial usage and navigation between the respondents. The approaches presented here match these requirements by using the visualisation power of Geographical Information Systems (GIS) and the application of methods prevalent in quantitative geography.

The conceptual foundation for all measures developed here is the enumeration of unique activity locations visited over the six weeks of reporting, the identification of routes and areas the persons have travelled through and the frequency of visit. The proposed approaches depend on two related statistical ideas: Probability and intensity / density. The latter one may furthermore be differentiated by the intensity of actual use and the intensity of the perception of the travel environment.

Figure 2 gives an overview and details the basic features as well as benefits of the three main approaches described further below. The approaches – which represent an evolution with a varying level of detail and comprehensiveness – are:

- a confidence ellipse (interval) approach which leads to a two-dimensional geometry around a suitably chosen centre point. This measures only uses the information about the locations visited and by construction assumes that the person knows all of the area covered by the ellipse, which is generally rather large because of the assumed functional form (ellipse).

- a kernel densities approach which again uses information about the locations, but is more restrictive in its spatial assumptions. Here only those areas are included which have been visited with a certain non-zero probability.

- a minimum spanning tree (network) methodology, i.e. the length of the minimum distance routes between the locations visited, or the area covered by a buffer around those routes.
Figure 2  Measuring activity spaces: Overview of basic concepts

a) Confidence ellipses

- Basic approach: Probability; smallest possible area in which a defined share of all visited locations is situated
- Measure: Size of area (plus direction of main axis)
- Special feature/quality: Shows dispersion of visited locations

b) Kernel densities

- Basic approach: Density surface; based on the proximity of activity locations
- Measures: a) Area covered exceeding a certain threshold value, b) “Volume”
- Special feature/quality: Represents local clusters / sub-centres within individual activity space

c) Minimum spanning trees (networks)

- Basic approach: Smallest possible geometry based on all observed origin-destination relations
- Measure: a) Length of tree, b) Size of buffered area around tree
- Special feature/quality: Indicator for the perception of urban space
3.1 Confidence ellipses

The first approach to capture the structure and size of human activity spaces is the estimation of confidence ellipses based on the observed distribution of activity locations (see Kachigan, 1991 for an introduction into the statistical basics). The measure correlates with a range of simpler measures of dispersion, such as the standard distance (see e.g. Schönfelder, 2001; Schönfelder and Axhausen, 2001 for applications to travel behaviour).

The confidence ellipse concept picks up existing approaches to visualise distributions used for example in biological habitat research (Jennrich and Turner, 1969; Southwood and Henderson, 2000) or in human geography (Bachi, 1981). As mentioned earlier, ellipses have been also used before to represent and measure potential action spaces (Saxena and Mokhtarian, 1997 for a recent example) or to visualise activity patterns based on (mainly) cross-sectional travel data (Boulahbal, 1997; Newsome, Walcott and Smith, 1998; Dijst, 1999). Furthermore, the development of the approach was inspired by the work of the 1970s UMOT project (Unified Mechanism of Travel) and which focused on the analysis of aggregate activity densities and the testing of hypotheses about the character of trip distributions at the regional level (Zahavi, 1979; Beckmann, Golob and Zahavi 1983a; 1983b). UMOT lead to the calculation of ellipse shaped travel probability fields which are the geometric result of travel demand, network structure (system supply) and the supply of activity opportunities (urban form).

**Mathematical basics and adaptations to travel behaviour analysis**

Confidence ellipses – also called prediction interval ellipses – are an explorative bivariate method to investigate the relationship between two variables. They are often used for hypotheses testing and to detect outliers. Confidence ellipses are analogous to the confidence interval of univariate distributions as the smallest possible (sub-)area in which the true value of the population should be found with a certain probability (e.g. 95%).

The calculation of the ellipses is tied to the assumption that the variables are bivariate-normal. This was shown earlier for the activity locations of travellers (Moore, 1970).

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3 An implementation of the confidence ellipse approach was recently integrated into the common GIS software ESRI ARCVIEW® (see Schwarze and Schönfelder, 2001).
The ellipses are computed with the covariance matrix of all points (activity locations) of a person

\[ S = \begin{pmatrix} s_{xx} & s_{xy} \\ s_{yx} & s_{yy} \end{pmatrix} \]

where each covariance is defined as

\[ s_{xx} = \frac{1}{n-2} \sum_{i=1}^{n} (x_i - \bar{x})^2 \]

\[ s_{yy} = \frac{1}{n-2} \sum_{i=1}^{n} (y_i - \bar{y})^2 \]

\[ s_{xy} = s_{yx} = \frac{1}{n-2} \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) \]

The determinant of the covariance matrix (generalised variance) is

\[ |S| = s_{xx}s_{yy} - s_{xy}^2 \]

with the ellipse size \( A \)

\[ A = 6\pi|S|^{\frac{1}{2}} \]

The orientation of the ellipse is determined by the sign of the linear correlation coefficient between the coordinates \( x \) and \( y \) of the activity locations; the longer axis of the ellipse is the regression line (Figure 2a).

In the context of spatial behaviour, confidence ellipses may be used as a description of activity location distributions in space. Furthermore, the size of the area is an indicator for the dispersion of visited locations and may be used to compare the dispersion between travellers or of one respondent on different days of the week.

As a first solution, the arithmetic mean – either of the all unique coordinates or the coordinates weighted by the frequency of visit – may be accepted as the centre of the activity space. It seems nevertheless necessary to modify this analytical geometrical concept to gain a behaviourally more realistic measure.
To reach this, one should consider two important characteristics of daily mobility: 1) the home location is the undoubted peg of daily mobility (see also Cullen and Godson, 1975) and 2) for most travellers it can be assumed that the geometric shape of the revealed activity patterns is ellipse-like with two focal points (see Dijst, 1999 for empirical findings). For weighted frequencies, the arithmetic mean is normally close to home but this location is not normally a relevant real-world address, though. For a modification of the base approach, these facts are taken into account by either substituting the arithmetic mean by the coordinate of the home location (alternatively any other important activity location visited) or even by two pegs as focal points of two separate ellipses.

Figure 3 shows examples of such modifications. First (a), ellipses are shown where the home locations substitute the mean point in the calculation of the covariance matrix. This figure indicates significant differences on the intra-personal level by weekdays and weekend. This is evident for the size of the fields, the location of the action spaces within the city and the main axes of the ellipses.

The second extension (b) is the creation of two ellipses covering the activity locations related to home (such as home-based grocery shopping) plus a further peg such as work. These ellipses may be merged to visualise and measure the spatial clustering of secondary activities such as grocery shopping around the pegs (see e.g. Holzapfel, 1980 for early findings on the locational effects of the separation of home location and work place).
Clearly, this adaptation is not consistent with the original mathematical definition but it allows a more plausible description of the travellers’ activity patterns. People usually do not move randomly about the fictitious spatial mean of their activity space – there is clear evidence that home is by far the most important focal point of daily life.

### 4.2 Kernel densities

As a second approach we propose the estimation of *Kernel densities* which considers activity space as the area with non-zero probability of activity performance. Kernel densities allow to explore the combined effects of locational choice and the frequency of visit. Again, the habitat research has applied kernel techniques to measure utilisation of animals (see Hooge, 2000; Kirkby, 2001).

The basic process behind the estimation of kernel densities is a transformation of a point pattern (such as a set of activity locations) into a continuous representation of density in a wider area. Generally speaking, the estimation is an interpolation or smoothing technique which generalises events or points to the area in which they are found. The interpolation then leads
to a calculation of a value for any point, cell or sub-region of the entire area which character-
ises the density or intensity of e.g. population or income per capita.

Kernel densities have been already applied successfully to large cross-sectional data sets
(Kwan, 2000; Buliung, 2001). Modern GIS applications include tools to calculate such den-
sity measures effectively, including 3D visualisations which impressively show space-time
interactions.

The estimation of the kernel densities was performed in the Geographical Information Systems
(GIS) ARCVIEW and ARCINFO. The GIS packages divide areas into a user definable number
of cells. The density values are assigned to all cells according to the kernel density estimated for
the underlying point pattern. Subsequently, the raster approach allows to easily aggregate local
densities to total density values for continuous space (see below).

There exist a variety of approaches for the actual density estimation (for an overview see Sil-
verman, 1986). Some of those estimation techniques are frequently used in quantitative geog-
raphy and other applied research areas (see Fotheringham, Brunsdon and Charlton, 2000).
Probably the most common approaches the fixed kernel method (also applied here). Similar to
histogram techniques, a symmetrical – variably distributed – kernel function is placed over
each data point. For all locations in the entire area (ℜ) – not only for the data points – the
overlapping values are summed which yields the density or intensity estimate (Figure 4). This
leads to a smoothing of the surface where the level of smoothness depends on the bandwidth
of the kernel function which is analogous to the width of ordinary histogram boxes. The
bandwidths may be varied according to the necessary degree of smoothness – with greater
smoothing at bigger bandwidths or values of the smoothing parameter. The GIS finally may
represent the resulting estimates for all grid cells as a continuous surface.

Considering a grid structure in which single points are substituted by grid cells, the base ker-
nel density is given by the formula:

$$\hat{\lambda}(s) = \sum_{d_i \leq \tau} K\left(\frac{d_i}{\tau}\right)$$

with

- $\hat{\lambda}$ density estimate at grid point $s$
- $\tau$ bandwidth or smoothing parameter
- $K$ kernel function (to be further specified)
- $d_i$ distance between grid point $s$ and the observation of the $i$th event
The kernel function $K$ itself may have different forms such as normal, triangular or quartic. The results do not differ significantly as long as the distribution is symmetrical. In the following, a quartic kernel function (see Mitchell, 1999 for details) is used which leads to the following kernel density

$$\lambda(s) = \sum_{d_i < \tau} K \left\{ \frac{3}{\tau^2 \pi} \left[ 1 - \frac{d_i^2}{\tau^2} \right]^2 \right\}$$

A particularity of the quartic function – e.g. compared to a normal distribution – is that outside the specified bandwidth $\tau$, the function is per definition set to zero – with implications for the behavioural model. This means that activity locations outside a specified radius do not contribute to the density estimation of the particular point (cell) in space. In other words, a quartic distribution of the kernel function adds weight to locations closer to the centre of the bandwidth than those further apart (see NedLevine and Associates, 1999 for characteristics of the different kernel forms).
Examples

Figure 5 shows the principle of the approach by visualising a kernel density grid around the workplace location of a Mobidrive Karlsruhe sub-sample respondent. The frequency of visit is considered as a (linear) weight.

It can be easily seen that – due to the quartic kernel function – the densities decrease with growing distance from the most frequently visited location(s). The size of the dots represent the number of visits over the six-week reporting period. The visual effect of the GIS output, i.e. the graduation of colours or the visual smoothness, depends very much on the grid cell size chosen. Principally, the sum value of total densities for the entire reference area is directly related to the grid cell size – this means that the quotient of the overall density divided by number of cells is the same for every setting. Consequently, a comparison of the activity spaces (size) of one person over time or between persons should be based on the same defaults for cell size, bandwidth or scale factors.

Figure 5 Out-of home activity density of one single Mobidrive respondent represented by kernel density estimates; aggregated over 6 weeks, Karlsruhe

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4 Unit scale factors are used by the GIS to convert the map units of the input point dataset (here: activity locations and the frequencies of visit) to different units. The ARCINFO default value is 1, which calculates density in units of number of points per one square map unit (e.g. m²). Considering the relatively great size of the reference areas (about 600km²) and the comparable low frequencies of visit for some of the locations, for the calculations of the next section of this study a high unit scale factor of 1.000 was chosen. This only affects the magnitude of the density results. Effectively, output grid values are multiplied by the square of the unit scale factor.
From a behavioural point of view, the selection of the bandwidth of the kernel function (search radius) is an important issue. It may be argued for the activity location data that the bandwidth reflects a maximum distance of spatial interactions between activity locations. One could raise the question which activity locations have a functional affiliation with each other in the understanding of people (e.g. home location and local groceries). In addition to that, what is the distance travellers accept to e.g. walk to the locations form home – indicating vicinity or familiarity with one’s neighbourhood. Hence, the choice of the bandwidth should contribute to a conceptual approach of proximity and neighbourhood in daily travel. For the following example and for the calculations in the next chapter, a bandwidth of 1000m was chosen which can be defined as the maximum walking distance which is accepted between two places (75% percentile of all observed walking distances).

In the following figure, kernel densities are visualised for selected days of the week of one MobiDrive respondent based on the reported activity locations in the first sub-figure. The visualisation represents both, the strong regularity in the activity space’s size and structure from Monday to Friday and significant changes during the weekend days. As home location and workplace are close together, high kernel densities are concentrated in the vicinity of these two mobility cores.
Beyond the powerful visualisation of the kernel densities, several relevant measures may be considered to quantify activity space sizes:

a) the extent of the *usage of space* is represented by the number of cells for which the density value exceeds a certain threshold (i.e. \( > 0 \))

b) the intensity of space usage given by the sum of the densities for all grid cells
c) measures a) / b) reduced by areas probably not open for ordinary activities, such heavy industrial or utility areas (see below).

Turning to measure (c), it can be argued the spatial supply (distribution) of activity opportunities is a further key factor for activity or trip demand and therefore for the shape of activity spaces. The availability of exact data covering the supply – such as digital point of interest data – is still limited and selective, though, which makes it difficult to relate travel supply and demand. Nevertheless, aggregate land use data which is available for both Mobidrive case study cities, at least yields information on areas of minimal interest for private travel such as agricultural land, industrial areas etc. Considering measure (a) or (b) as activity space indicators, one could introduce such areas of no interest to tailor the area to a more likely shape (Figure 7). Sure, this is connected with a further uncertainty about the actual usage of urban space as it remains unclear if the definition of potential exclusion areas varies for the different respondents. Still, the proposed approach is a further methodological step to capture the observed activity patterns of individuals over time.

Figure 7 Area of no interest: Agriculture, utility and disposal areas (grey shading)

4.3 Minimum spanning trees (networks)

The activity densities presented above pretend that travellers have a spatially continuous knowledge or even make use of a continuous urban space around the activity locations visited – which is even more true for the ellipse measure introduced at the beginning. This is a simplification of human behaviour as the identified areas are certainly not used in a literal way.
Furthermore, the potential knowledge of activity locations or landmarks is probably overestimated – depending on the chosen bandwidth of the kernel function.

By introducing a further measure of activity space characteristics, we want to acknowledge that transport network structures shape the travellers’ perception of potential activity locations as well as the knowledge of place and the spatial orientation (Golledge, 1999). Hence, calculating the size as well as visualising the shape of human activity spaces should be oriented towards the paths chosen by the travellers.

One possibility to consider the network supply-travel interactions is to identify the part of the network which was actually used by the Mobidrive respondents during the six weeks of reporting. This particular portion and the roads’ adjacent built environment can be assumed to be known by the traveller dependent on the frequency of usage. The identification of the network links needs to rely initially on assumptions about the chosen routes, though, as the survey design did not capture the path choices. As an approximation, the shortest route for each unique relation reported by the Mobidrive respondents was calculated – based on the individual 6-week origin-destination matrix and available road network. Enhancements of this procedure are imaginable, e.g. by substituting the deterministic shortest path algorithm by a probabilistic one (see Sheffi, 1985; Bovy, 1996). Furthermore, the paths chosen can be properly assigned to the different modal networks according to the modes actually chosen for the different trips.

The initial application of the concept is leading to a geometry which can be compared to a minimum spanning tree (Figure 8) – well known from the graph theory. The structure and size of the tree is a further quantitative indicator for the perception, knowledge and especially the usage of urban space. Considering the perception of the (built) environment, it can be assumed that there is considerable correlation between the frequency of using a network link and the knowledge of the surrounding area. It is widely agreed by psychologists and geographers that travelling through an environment is the common way of spatial learning and acquiring spatial expertise (Golledge, 1999).

What can be especially seen from the first of the two examples in Figure 8 is that again the home location is the major hub for daily life travel acting as a central node in the given road network. This was expected as the share of complex trip chains is much smaller than the amount of simple home-based trips, such as home-work-home, home-shop-home or home-leisure-home. More than 70% of all Mobidrive journeys involve only one out-of-home activity.
The concept can be extended from a measure of the total length of the tree to an areal measure by buffering around the links of tree (see Figure 9). The exemplary visualisation nicely shows both, the primary node effect with a relatively large and intensively used area around the traveller’s home location as well as the areas of probably less or no knowledge (grey shading). The identified area of potential perception widens around home (Figure 9b) with several further visited activity locations and narrows along the links to the other (main) activity centres. A calculation of the size of the known/perceived area is possible.
INTERACTIONS BETWEEN THE MEASURES AND SELECTED SOCIODEMOGRAPHIC FACTORS

The presentation of the measures showed that each of them has its certain qualities and limitations. A purposeful selection of one of the measures in a applied setting needs to account for the particular behavioural aspect which is stressed by the indicators and what interactions exist between the measures. Although the input data is the same for the development of each measure (i.e. the locational choice and number of visits), the calculation results differ considerably. This is due to their particular sensitivities towards the frequency of visit, neighbourhood effects and outliers.

A large amount of the variation in the size of individual activity spaces can be explained merely by the amount of travel observed. But number of trips can only function as a proxy if the number of locations and the size of the activity space grows with it. Many trips to one or few locations, even if widely spread would not automatically indicate a large activity space in the sense of the perception, knowledge or acquisition of (continuous) space.

Relating the measures with each other and with the amount of travel is a way of better identifying the character as well as the distinct strengths and weaknesses of the measures (Table 1). Turning to the relationship with the amount of travel at first, there are strong effects on the volume indicator with an almost 100% correlation. At first sight, this findings seem to be unattractive. One could ask if an indicator for the size of individual activity spaces is useful which tells us that the structures of spatial mobility are tied to the pure amount of travel? At the same time, though, the measure and the outcome of the investigation strongly confirms our expectations. It indicates that the usage as well as the up-to-date knowledge or urban space is a function of the amount of contact a traveller has.

The other measures show less definite correlations with the travel volume but still there are considerable positive effects. The confidence ellipse which is the simplest measure from a behavioural point of view shows the smallest interactions with both, the total of number of trips and the amount of unique locations visited. This is a sign that geographical location and therefore also the effect of outliers is an important determinant for the ellipse size which potentially over-represents human activity spaces.

Turning to the relationships between the measures, it is evident that there is strong correlation between the kernel area measure and the length of the minimum spanning network and – less
strongly – between the network length and the ellipse size. This mainly shows that the density area – at least at this local level of analysis – both represents well the core contact space of the respondents but also the space in which people move and navigate, i.e. the area between the core locations. If one wishes to learn more about the intensity of the usage of those areas, one has to turn to the kernel and network measures weighted by frequency – which again have a visible correlation with each other.

Table 1  Pearson correlation coefficients between the amount of travel and the size measures (Karlsruhe only)

<table>
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<th></th>
<th>Number of trips</th>
<th>Number of unique locations</th>
<th>95% confidence ellipses (weighted), local trips only</th>
<th>Area with positive kernel activity density estimate (unweighted)</th>
<th>Volume with positive kernel activity density estimate</th>
<th>Length of MSN (unweighted)</th>
<th>Length of MSN (weighted by number of journeys)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of trips</td>
<td>0.68</td>
<td>0.53</td>
<td>0.98</td>
<td>0.45</td>
<td>0.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of unique locations</td>
<td>0.22</td>
<td>0.74</td>
<td>0.63</td>
<td>0.70</td>
<td>0.76</td>
<td></td>
<td></td>
</tr>
<tr>
<td>95% confidence ellipses (weighted), local trips only</td>
<td>0.39</td>
<td></td>
<td></td>
<td>0.65</td>
<td>0.59</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Area with positive kernel activity density estimate (unweighted)</td>
<td>0.49</td>
<td></td>
<td></td>
<td>0.78</td>
<td>0.81</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volume with positive kernel activity density estimate</td>
<td>0.39</td>
<td></td>
<td></td>
<td>0.50</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Length of Minimum spanning network (unweighted)</td>
<td>0.93</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>159</td>
<td>159</td>
<td>159</td>
<td>159</td>
<td>159</td>
<td>159</td>
<td>159</td>
</tr>
</tbody>
</table>

All correlations shown are significant at the 0.05 level (2-tailed).
Selected empirical results

The visualisation example above already indicated that there is behavioural variability between the days of the week of a single traveller and between respondents of certain sociodemographic groups. In the following, selected results are presented which confirm the findings and demonstrate the suitability of the developed indicators.

The Mobidrive sample contains a wide range of respondents in terms of income, home location within the urban area and ownership of mobility tools (vehicles and public transport season tickets). Table 2 summarises these differences for the two cities and two selected measures of activity spaces size (the area with a positive kernel activity density estimate [in 500*500 meter grid units] and length of minimum spanning network [km] weighted by the number of journeys). These two were chosen to represent the different approaches (See Table 1 for the correlation structure between the measures).

The significant differences vary according to measure, as these stress different elements of the observed behaviour. For the kernel density measure significant differences are detectable for part-time workers and those, who are the main user of a car. For the minimum spanning network measure some income groups and some age groups are different.
Table 2  Average size of activity space by socio-demographic characteristics

<table>
<thead>
<tr>
<th></th>
<th>City</th>
<th>Both cities</th>
<th>Karlsruhe</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Karlsruhe</td>
<td>Halle</td>
<td></td>
<td>Area with</td>
<td>Area with</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>positive kernel</td>
<td>positive kernel</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>density estimate</td>
<td>density estimate</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(unweighted)</td>
<td>(unweighted)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Length of minimum</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>spanning network</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(weighted)</td>
<td></td>
</tr>
<tr>
<td>[Number of 500*500 m grid units]</td>
<td>[km]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>129</td>
<td>107</td>
<td>118</td>
<td>237</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>120</td>
<td>112</td>
<td>116</td>
<td>227</td>
<td></td>
</tr>
<tr>
<td>Income per adjusted head</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Up to 2000 DM</td>
<td>113</td>
<td>110</td>
<td>111</td>
<td>208</td>
<td></td>
</tr>
<tr>
<td>2 to 3000 DM</td>
<td>134</td>
<td>104</td>
<td>119</td>
<td>236</td>
<td></td>
</tr>
<tr>
<td>3 to 4000 DM</td>
<td>117</td>
<td>133</td>
<td>122</td>
<td>218</td>
<td></td>
</tr>
<tr>
<td>4000 DM and more</td>
<td>127</td>
<td>113</td>
<td>122</td>
<td>274</td>
<td></td>
</tr>
<tr>
<td>Main car user</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>116</td>
<td>105</td>
<td>110</td>
<td>204</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>135</td>
<td>117</td>
<td>127</td>
<td>268</td>
<td></td>
</tr>
<tr>
<td>Season ticket local PT</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>127</td>
<td>111</td>
<td>118</td>
<td>242</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>121</td>
<td>104</td>
<td>114</td>
<td>214</td>
<td></td>
</tr>
<tr>
<td>Working hours</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Up to 10 h/week</td>
<td>116</td>
<td>103</td>
<td>109</td>
<td>192</td>
<td></td>
</tr>
<tr>
<td>10 to 35 h/week</td>
<td>138</td>
<td>149</td>
<td>141</td>
<td>279</td>
<td></td>
</tr>
<tr>
<td>35 and more h/week</td>
<td>129</td>
<td>111</td>
<td>120</td>
<td>260</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Up to 17 years</td>
<td>118</td>
<td>87</td>
<td>102</td>
<td>206</td>
<td></td>
</tr>
<tr>
<td>18 to 29 Years</td>
<td>110</td>
<td>130</td>
<td>120</td>
<td>212</td>
<td></td>
</tr>
<tr>
<td>30 to 44 years</td>
<td>141</td>
<td>112</td>
<td>126</td>
<td>283</td>
<td></td>
</tr>
<tr>
<td>45 to 59 years</td>
<td>128</td>
<td>115</td>
<td>122</td>
<td>252</td>
<td></td>
</tr>
<tr>
<td>60 years and older</td>
<td>113</td>
<td>106</td>
<td>110</td>
<td>171</td>
<td></td>
</tr>
</tbody>
</table>

Excluding respondents with less than 40 trips over the six-week reporting period
Still, there is no pattern recognisable, that certain person groups e.g. those associated with social disadvantage or handicapped mobility: the female, the old, those with low incomes are significantly different from the rest of sample.

The reverse analysis confirms this impression. For Table 3 the respondents were grouped into four classes, each representing a quarter of the distribution in each city. The quartiles were defined with respect to the distribution of the activity spaces as measured by the areas with positive densities. For each class the average value or share of the most important variables was calculated. There are some significant differences, but none concerning variables associated with social exclusion (income, age, sex). There are more parents in the highest quartile, respondents in the lower half of the distribution report fewer working hours than those in the highest quartile; they have equally fewer driving licences; those in the lowest quartile are also in comparison with the highest quartile less likely to be the main users of a car.

Table 3  Socio-demographic profiles of the respondents by quartiles of the activity size distribution (areas with positive kernel density estimates)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Male Share</td>
<td>48.1</td>
<td>52.5</td>
<td>56.1</td>
<td>41.9</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Standard Error</td>
<td>5.6</td>
<td>5.6</td>
<td>5.5</td>
<td>5.8</td>
</tr>
<tr>
<td>Age Mean</td>
<td>39.062</td>
<td>39.525</td>
<td>39.110</td>
<td>42.770</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Standard Error of Mean</td>
<td>2.306</td>
<td>2.329</td>
<td>2.102</td>
<td>1.617</td>
</tr>
<tr>
<td>Parent Share</td>
<td>22.2</td>
<td>28.8</td>
<td>29.3</td>
<td>51.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Standard Error</td>
<td>4.6</td>
<td>5.1</td>
<td>5.1</td>
<td>5.8</td>
</tr>
<tr>
<td>Number of working hours Mean</td>
<td>16.315</td>
<td>17.079</td>
<td>17.805</td>
<td>23.779</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Standard Error of Mean</td>
<td>2.341</td>
<td>2.281</td>
<td>2.334</td>
<td>2.541</td>
</tr>
<tr>
<td>Drivers licence Share</td>
<td>53.1</td>
<td>63.8</td>
<td>70.7</td>
<td>81.1</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Standard Error</td>
<td>5.6</td>
<td>5.4</td>
<td>5.1</td>
<td>4.6</td>
</tr>
<tr>
<td>Main user of a car Share</td>
<td>28.4</td>
<td>40.0</td>
<td>43.9</td>
<td>51.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Standard Error</td>
<td>5.0</td>
<td>5.5</td>
<td>5.5</td>
<td>5.8</td>
</tr>
<tr>
<td>Household income Mean [DM]</td>
<td>4242</td>
<td>4804</td>
<td>4160</td>
<td>4377</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Standard Error of Mean</td>
<td>255</td>
<td>247</td>
<td>226</td>
<td>229</td>
</tr>
</tbody>
</table>

Another possible determinant of activity space size is the household’s relative location. Although both case study areas are cities only of about 200.000 – 300.000 inhabitants, a suburb-
\textit{bia effect} is visible – at least for the confidence ellipse measure. Travellers of households with locations at the edge of the cities show considerably more dispersed activity spaces than more central households – for both, weekdays and the weekend days. It is interesting, though, that the effect is not necessarily a linear one as for weekdays the sizes of ellipses for the lower categories (up to app. 6km distance from CBD) are close together. These findings are only a starting point, though, as the sub-group of the peripheral households is small for both cities (Karlsruhe: 6, Halle: 4).

Figure 10    Household location as determinant for activity space size (95\% confidence ellipse)

Finally turning to the \textit{minimum spanning tree} measure, the length of the geometry as well as the differences between the sociodemographic groups are in the centre of the analysis. The measure gives the sum of length of the used network links. At this stage of the work, the measure is available for Karlsruhe only and considers link lengths of the regional road network.

There are two main interrelated factors influencing the spanning tree’s characteristic (Table 8). First, the size of the tree is affected by the spatial dispersion of the places visited. The measure therefore reflects the dispersion of the activity pattern – in parallel with the other measures. Second, the weighted geometry (link length multiplied by frequency of usage) is directly bound to the overall group-specific travel demand. The differences of tree lengths be-
tween the sociodemographic groups confirm the common findings on the determinants of travel demand. The coefficient of variation (standard deviation / mean * 100) indicates that the relative variation is high for students, whereas the group-specific distribution of the measure is in particular low for fulltime workers with more similar daily activity patterns compared to the others.

Table 4  Minimum spanning trees (networks) characteristics

<table>
<thead>
<tr>
<th>Occupation status</th>
<th>N</th>
<th>Mean number of trips 6 weeks (Std.)</th>
<th>Mean number of unique locations (Std.)</th>
<th>Mean unweighted** tree length [km] (Std.)</th>
<th>Mean ratio weighted / unweighted tree length</th>
<th>Std.</th>
<th>Coeff. Var. [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pupil</td>
<td>27</td>
<td>157 (43)</td>
<td>23 (6)</td>
<td>68 (31)</td>
<td>2.77</td>
<td>0.75</td>
<td>27</td>
</tr>
<tr>
<td>Student</td>
<td>7</td>
<td>108 (91)</td>
<td>24 (15)</td>
<td>79 (43)</td>
<td>2.32</td>
<td>0.88</td>
<td>38</td>
</tr>
<tr>
<td>Apprentee</td>
<td>6</td>
<td>182 (79)</td>
<td>30 (12)</td>
<td>72 (26)</td>
<td>3.31</td>
<td>1.01</td>
<td>30</td>
</tr>
<tr>
<td>Housemaker</td>
<td>10</td>
<td>154 (65)</td>
<td>29 (11)</td>
<td>94 (45)</td>
<td>3.25</td>
<td>0.74</td>
<td>23</td>
</tr>
<tr>
<td>Retiree</td>
<td>28</td>
<td>129 (58)</td>
<td>25 (10)</td>
<td>66 (32)</td>
<td>3.06</td>
<td>0.94</td>
<td>29</td>
</tr>
<tr>
<td>Unemployed</td>
<td>1</td>
<td>59 (-)</td>
<td>8 (-)</td>
<td>13 (-)</td>
<td>1.99</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Parttime</td>
<td>21</td>
<td>161 (49)</td>
<td>32 (12)</td>
<td>91 (36)</td>
<td>3.07</td>
<td>0.76</td>
<td>25</td>
</tr>
<tr>
<td>Fulltime</td>
<td>47</td>
<td>141 (46)</td>
<td>26 (10)</td>
<td>74 (36)</td>
<td>3.07</td>
<td>0.72</td>
<td>23</td>
</tr>
<tr>
<td>Self-employed</td>
<td>8</td>
<td>188 (47)</td>
<td>37 (10)</td>
<td>110 (49)</td>
<td>3.61</td>
<td>1.11</td>
<td>31</td>
</tr>
</tbody>
</table>

* Including home

** “Unweighted”: Total link length of tree, “weighted”: link lengths multiplied by frequency of usage

+ City of Karlsruhe only

Summarising these initial comparisons and empirical results, the characteristics of the measures may be concluded as follows: The first indicator, the confidence ellipse overgeneralises the spatial patterns through its rigid assumptions: the size estimated is therefore too high. The kernel density derived measures focus on the vicinity of the various locations to each other, but ignore their spread across the landscape. They permit isolated islands of activity, thereby ignoring the connections between those. The minimum spanning networks stress, on the other hand, the spatial spread of the activities in the study area by measuring the length of the routes between the locations.
5 CONCLUSIONS

The paper has introduced a number of approaches to measure the size of human activity spaces: starting with a measure transferred from biology, but then suggesting new approaches. These measure have become possible for the first time, as only now data sets have become available for humans which are long enough to allow this estimation at the personal level.

Recognising the weaknesses of the measures such as the over-scaling of the actually frequented urban areas or the assumption of the continuousness of space usage, we believe that the development of the measures is a substantial contribution to the analysis of travel behaviour. As for other analysis tasks based on the unique Mobidrive longitudinal data set, there are only few indicators for the stability and variability of travel behaviour available. The conceptualisation of the measures reflects the travel research’s intention to combine the existing theories on spatial behaviour and knowledge acquisition with empirical analysis. Based on the Mobidrive data which yields respondents’ information on a day-to-day basis, this is possible for the first time in this particular field of behavioural analysis.

To sum up, the developed measures are powerful for several reasons:

- The measures are flexible and allow the researchers to chose the parameters (e.g. the choice of mean point of the confidence ellipse or the kernel bandwidths) according to the particular analysis interest.

- The implementation of the measurement is possible within common GIS software packages.

- The visualisation of the examples is straightforward and enables practitioners to gain an insight into the travellers’ mobility routines.

- The proposed enhancements (minimum spanning trees, no-go-areas) nicely take into account the interaction between activity location supply and destination choice.

Future work will be focused more strongly on the implementation and the application of the proposed measures as well as on a further improvement of the representation of the behavioural reality.

The initial results yield a relevant background for the discussion of transport policy and planning issues. From our point of view, two aspects are of a particular potential impact:
On the one hand, the enumeration of daily-life activity locations and the analysis of the distribution of such places reveals both, the supply structure of activity opportunities in space and the destination choice behaviour of travellers given their perceived supply. This invites transport planning and research to once more evaluate present and imaginable future urban structures from the perspective of sustainable transport policy. This includes for example measures to increase the amount of the opportunities (i.e. potential destinations) to satisfy the activity demand in the household’s neighbourhood which eventually reduces travel expenses, further congestion and emissions. There is evidence that local accessibility oriented land-use planning matters (Banister, 2000; Simma, 2000). We do not neglect, though, that the there are complexity and non-linearities within the interaction between locational supply and the actual choice of destinations.

On the other hand, the activity space issue has to be put on the agenda when discussing the relationship between poverty, the deprivation of urban areas and transport. Kenyon, Lyons and Rafferty (2002) argue that important determinants of the activity space such as poor or unavailable transport (e.g. car ownership) as well as reduced accessibility to facilities, goods and services are dimensions and factors of social exclusion. The size and structure of the activity space therefore may act as a – highly political – indicator of social justice and the efficiency of a infrastructure supply policy matching societal needs.
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