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ORIGINAL ARTICLE

Activity triangles: a new approach to measure activity spaces

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Abstract

There is an on-going challenge to describe, analyse and visualise the actual and potential extent of human spatial behaviour. The concept of an activity space has been used to examine how people interact with their environment and how the actual or potential spatial extent of individual spatial behaviour can be defined. In this paper, we introduce a new method for measuring activity spaces. We first focus on the definitions and the applications of activity space measures, identifying their respective limitations. We then present our new method, which is based on the theoretical concept of significant locations, that is, places where people spent most of their time. We identify locations of significant places from GPS trajectories and define the activity space of an individual as a set of the first three significant places forming a so-called "activity triangle". Our new method links the distances travelled for different activities to whether or not people group their activities, which is not possible using existing methods of measuring activity spaces. We test our method on data from a GPS-based travel survey across three towns is Scotland and look at the variations in size and shape of the designed activity triangle among people of different age and gender. We also compare our activity triangle with five other activity spaces and conclude by providing possible routes for improvement of activity space measures when using real human movement data (GPS data).

Keywords Activity space · Activity triangle · GPS movement data · Human mobility · Significant locations

Mathematics Subject Classification 65C20

1 Introduction

Understanding the travel behaviour of individuals and the spatial extent of their activities (activity spaces) is crucially important for transportation planning, capacity of neighbourhoods and mobility studies (Manaugh and El-Geneidy 2012). The

Extended author information available on the last page of the article concept of an activity space has been used to examine how people's habitual movements interact with their environment and how the actual or potential spatial extent of individual spatial behaviour can be defined (Golledge and Stimson 1997; Weber and Kwan 2002; Tribby et al. 2016). An activity space is the limited part of an environment explored by an individual over a defined period of time such as a day, month, year or a lifetime. In other words, it is the geographic coverage of places and routes that people visit and undertake (Hirsch et al. 2014; Lee et al. 2016).

Many researchers and policy-makers claim that the context of neighbourhoods and their influence on day-to-day lives forms a crucial part of people's travel behaviour (Golledge and Stimson 1997; Kamruzzaman and Hine 2012). Theories about neighbourhood effects, social segregation and exclusion assume that neighbourhoods and their socio-demographic characteristics operate to influence different groups of people (for example women, children, and different ethnic groups) through exposure-based mechanisms (Casas and Arce 1999; Schönfelder and Axhausen 2003; Wong and Shaw 2011; Palmer et al. 2013). Identifying activity spaces therefore makes it possible to investigate a number of research questions critical for understanding urban neighbourhood problems (Browning and Soller 2014; Silm and Ahas 2014). Furthermore, understanding how individuals use cities and various facilities within them to perform their daily activities has important implications for urban policy making (Buliung and Kanaroglou 2006), and there has been a large amount of research undertaken to calculate accessibility to various services (Casas and Arce 1999; Neutens et al. 2012). Accessibility can be treated as either good or bad exposure to different services (Kestens et al. 2012) or as a binary factor of particular places (either places are or are not accessible) (Nemet and Bailey 2000; Vallée et al. 2010). The activity space concept can also be used to measure transport disadvantages and transport demand (Kamruzzaman and Hine 2012; Miranda-Moreno et al. 2012). The effect of built environment components on human mobility behaviour could further be used for analysing urban sprawl (Harding 2012).

Travel behaviour of an individual can be expressed as a sequence of activities and movements in time and space (Stopher et al. 2007). Investigating the structure of this behaviour has long been restricted by the absence of suitable data and methods to treat such data (Siła-Nowicka and Fotheringham 2019). In the existing literature, measuring activity spaces is based on information derived from travel diaries, origin–destination surveys and various travel and behavioural surveys (Chen et al. 2017; Smith et al. 2019). There are still only a few examples of using GPS movement data. The first attempts were made by Schönfelder and Axhausen (2002) who adapted activity space measures to examine differences in the travel behaviour of people from different neighbourhoods. GPS movement data were used to identify exposure to pollution, hazards or fast food and off-licence store locations (Zenk et al. 2011; Freisthler et al. 2014; Wei et al. 2018; Wang et al. 2018; Wang and Kwan 2018), and to examine accessibility to the health centres (Rainham et al. 2010). Further examples of the use of GPS-based activity spaces include the measurement of the levels of mobility of older adults (Hirsch et al. 2014, 2015), studying spatial patterns of homeless people (Šimon et al. 2019) as well as understanding segregation processes among residents of various types of housing (Zhang et al. 2019). Even though there have already been uses of GPS data for calculating activity spaces, recent research suggests that the potential of this type of data has not been fully realised. Sherman et al. (2005) described various ways of calculating activity spaces for data from more than 2000 individuals where GPS data were available but were not really used to calculate the activity spaces. Similarly, Rainham et al. (2010) and Hirsch et al. (2014, 2015) calculate activity spaces without prior processing or semantically enriching the GPS data. To the best of our knowledge, none of these studies explored the relationships between individuals' significant locations, their relative locations and the distances travelled between them.

In this paper, we take the geographer's approach, as described by Golledge and Stimson (1997), "geographers became experts on describing 'what' there is and are now seeking to explain 'why' or 'how' things were there". We therefore, try to seek answers for the "how" by analysing the extent of human spatial behaviour using mobility data. To do so, we introduce a new activity space measure, the activity triangle, that allows us to understand how different activities within a person's normal daily routine (spatio-temporal regularities in people's lives) are related to each other. In particular, the new measure lets us explore relationships between significant locations in the daily lives of individuals, something that is not possible using more traditional activity space measures.

The remainder of the paper is structured as follows: The next section introduces the related literature, then we present the methods, including the study area, the data and the definition of the new activity space measure. We then present an application of the method using GPS tracking high-frequency movement data, comparison of the methods and conclude with a discussion of major findings and future possibilities.

2 Background

The activity space concept was first proposed by Lewin (1951), as a "lifespace". A more formal definition was introduced by Horton and Reynolds (1971) and Brown and Moore (1970) almost simultaneously. Horton and Reynolds define activity space as a part of action space, whereas Brown and Moore refer to it as awareness space or an aspiration region. There are many other terms used in the literature to describe similar concepts: Beckman et al. (1983) define an activity space as a travel probability field; Hurst (1969) as a movement space; Dijst (1999) describes the concept as an actual action space, Schönfelder and Axhausen (2003) as an observed activity space, and Rai et al. (2007) as a locational choice of travellers. For the detailed literature review where more definitions and applications are depicted, see Patterson and Farber (2015).

Activity space concepts play a crucial role in quantitative analysis and descriptions of individual and group spatial behaviour (Patterson and Farber 2015). Even though the concept originates from travel behaviour and transport geography, there is considerable interest in the concept in other disciplines such as health and epidemiology. In public health and medicine, the idea of an activity space has been used to investigate the accessibility of health centres following evidence that long distances to healthcare facilities can restrict their use (Kwan 2013). The concepts have also been central in promoting healthy lifestyles (Shannon 1948; Maas 2008; Vallée et al. 2010; Lee et al. 2016), understanding the spreading of various diseases (Eryando et al. 2012; Perchoux et al. 2013) and environmental exposure (Jankowska et al. 2015). In criminology, it has been used to investigate spatial patterns of crimes (Brantingham and Brantingham 1993; Bichler et al. 2011); in demography, to examine the variations in demographics in different neighbourhoods and instances of social exclusion (Schönfelder and Axhausen 2003; Jones and Pebley 2014); and in urban planning to analyse exposure to different built environment characteristics and mixed land-use influences (Newsome et al. 1998; Handy and Boarnet 2002; Buliung and Kanaroglou 2006).

Numerous quantitative measures have been proposed as an approximation of an individual's activity space—here, we review the most commonly used ones (Table 1). Following Patterson and Farber (2015), we have divided these methods into six groups: ellipses, minimum convex hull geometries, kernel density approaches, network-based approaches (spanning trees), activity locations and others. Figure 1 provides examples of these six common activity space measures, calculated on the same GPS trajectory. For privacy reasons, there is no basemap provided for the representative person's activity spaces generated by different methods. The first panel (a) shows a confidence ellipse, a standard deviational ellipse (SDE), a weighted version of SDE, minimum convex polygon and a road network buffer and panel (b) shows a measure based on the kernel density estimation (KDE) surface.

Ellipse-based methods (confidence ellipse, SDEs and others) are used to describe and visualise the geographical distribution by summarising dispersion and orientation of movement patterns. MCP is represented by a smallest polygon (aka "fence") containing all the activity locations. KDE methods estimate kernel densities around activity points to demonstrate the intensity of these activities in space (Kwan 2000a). A set of identified locations such as home, work and social places (Hummon and Oldenburg 1991; Liao et al. 2007) can be used to study significant for individuals places. Network-based methods rely on calculating the shortest path between activity locations and creating a buffer around this potential path in order to determine an activity space (Hirsch et al. 2015). Wong and Shaw (2011) adopted a combination of MCP and Euclidean shortest path between visited points to define their activity space which was used to define indices to measure segregation. Context-based crystal growth—CCG and environmental context cube—ECC are based on a dynamic framework that represents and integrates daily movements and environmental context in a form of crystal-growth space (Wang et al. 2018) or space time cube (Wang and Kwan 2018).

To understand the differences between different measures of activity spaces, some comparative studies were undertaken (Schönfelder and Axhausen 2003; Rai et al. 2007; Kamruzzaman and Hine 2012; Manaugh and El-Geneidy 2012; Hirsch et al. 2015; Park and Kwan 2017; Hasanzadeh et al. 2018; Laatikainen et al. 2018). Their results indicate that there is not a single best method for all purposes and that results from each method vary depending on the particular task. Ellipses and minimum convex polygons generalise the pattern of activities, and their size is overestimated and therefore does not accurately represent individuals' behaviour and use of space (Schönfelder and Axhausen 2003; Chaix et al. 2012; Shareck et al. 2013,

Table 1 Activity space types with examples of their applications

Type	Activity space type	Literature	Application purpose	Measures
Ellipses	Confidence ellipse	Friendly et al. (2013)	Spatial behaviour	Shape/size
	Standard deviational ellipse (SDE)	Schönfelder and Axhausen (2003); Buliung and Kanaroglou (2006); Miranda-Moreno et al. (2012); Järv et al. (2014); Crawford et al. (2014); Li et al. (2015); Liu et al. (2015)	Spatial behaviour, factors, exclusion	Shape/size
	Ellipse-like forms—Home-Work ellipse	Newsome et al. (1998); Botte and Olaru (2010)	Spatial behaviour	Size
Minimum convex hull geometries	Minimum convex polygon—MCP	Buliung and Kanaroglou (2006); Kamruzzaman and Hine (2012); Manaugh and El-Geneidy (2012); Lee et al. (2016); Tana et al. (2016)	Spatial behaviour, shopping behaviour, transport disadvantage and exposure	Shape/size
Kernel density approaches	Kernel density estimation—KDE	Golledge and Stimson (1997); Kwan (2000b); Umair et al. (2014) Schönfelder and Axhausen (2003); Chaix et al. (2012); Perchoux et al. (2016); Šimon et al. (2019)	Spatial behaviour, intensity of behaviour, exposure, accessibility	Intensity
Network-based approaches	Network-based buffer	Hirsch et al. (2015)	Accessibility, spatial behaviour	Size/shape
	Total distance travelled	Páez et al. (2010)	Segregation, exposure	Size
Activity locations	Activity locations and significant locations	Liao et al. (2007); Bhattacharya et al. (2012); Siła-Nowicka et al. (2016)	Spatial behaviour	Number/ significance
Others	Environmental context cube—ECC	Wang and Kwan (2018)	Environmental exposure	Exposure parameter
	Context-based crystal growth activity space—CCG	Wang et al. (2018)	Environmental exposure	Growth extent
	Point-based linked neighbourhoods	Wong and Shaw (2011)	Segregation, exposure	Number (of people)

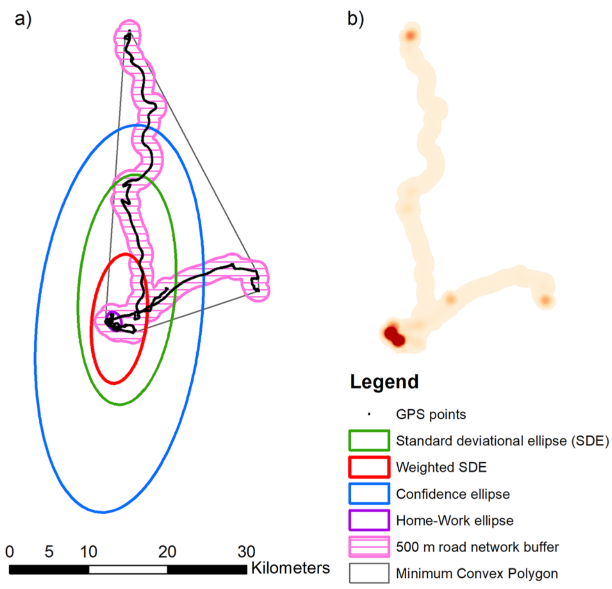

Fig. 1 An example of activity spaces calculated for one individual from the GPS-based travel survey

2014). Additional problems can arise when using GPS data (instead of a limited set of visited locations from a travel survey) to define a convex hull of an individual, as the minimum polygon would cover all the GPS traces of the individual, increasing the potential area of an activity space. This might however be seen as good or bad depending on the purpose of study. In comparison with the standard data derived from travel questionnaires, GPS convex hulls present a full spectrum of movement, e.g. daily mobility and not just places of activity.

Measuring the size of an activity space remains challenging (Harding 2012; Miranda-Moreno et al. 2012; Manaugh and El-Geneidy 2012). A large activity space may indicate a positive or a negative outcome depending on the subject of measurement. For example, when social exclusion is measured with activity spaces, the smaller activity spaces represent higher social exclusion (Schönfelder and Axhausen 2003). Conversely, when we measure transportation demand using the size of activity space as an indicator asserting that the smaller the area of activity space, the more public transport facilities in this area, and better managed transportation system (Botte and Olaru 2010). Small activity spaces are assumed to indicate that all the required facilities are close to an individual, and therefore, the accessibility of the place is high (Kamruzzaman and Hine 2012).

Several authors point out that the use of area to describe activity space might not be sufficiently informative (Manaugh and El-Geneidy 2012; Patterson and Farber 2015; Hasanzadeh 2019). Activity spaces with identical areas can have totally different shapes (Manaugh and El-Geneidy 2012). To improve the measure of activity spaces, an additional indicator of compactness, called fullness or circularity, was incorporated into a small number of studies (Harding 2012; Miranda-Moreno et al. 2012). This is a commonly used measure in geometry showing the ratio between the area of a circle with diameter equal to the diameter of a potential activity space, and the area of the activity space. Another measure that could be used for the same purpose is the ratio of the length of the minor and major axes of ellipses (Newsome et al. 1998). A low number shows a compact (usually dense) and relatively thin activity space. Furthermore, average distance to different destinations, elongation and an index of eccentricity can be used to study overall dispersion of a studied activity space (Hasanzadeh 2019). When measuring activity space from standard travel survey data using network-based approaches, the potential areas or lengths and structure of the covered road network are calculated using shortest path algorithms. However, in reality, humans do not always follow shortest paths due to their habits, prior knowledge about road conditions, real-time traffic situations (e.g. as increasingly available through Google or other tracking services) or other reasons affecting their decisions while making a trip (Schönfelder and Axhausen 2003).

In summary, most activity spaces developed to date focus on geometric characteristics describing the size and compactness of an activity space. These measures can be unreliable because size is usually overestimated. Also, none of these measures considers the relationships between travelled distances and the significant locations of individuals. Mobility can be seen as an essential factor shaping people's daily activity patterns (Vilhelmson 1999). Commuting distances and distances to places of other daily or weekly activities are associated with people's well-being and health (Christian 2012). Integrating this relationship into an activity space can help understand the level of accessibility in a given location and inform us about people's daily routines without breaching privacy.

3 Data and pre-processing

To develop a new form of activity space measure, we use GPS data from a travel survey in three towns in Fife in Scotland: Dunfermline, Glenrothes and Kirkcaldy. These towns were selected based on their different socio-economic characteristics and varying commuting patterns. Dunfermline is a commuter town for Edinburgh (20 km), Glenrothes lies between Dundee and Edinburgh (50 km to each), and Kirkcaldy is an industrial town located 30 km north of Edinburgh. The travel survey of volunteers from the three towns was conducted between October and November 2013 when participants were asked to carry a GPS device for a period of seven consecutive days. We used i-Blue 747 ProS GPS loggers and gathered data from 205 participants (127 men and 78 women), resulting in trajectories comprising of 3,869,831 raw GPS locations (Fig. 2). As the data come from the volunteers, the sample is not representative of the population in the three study areas. For more details about these data see (Siła-Nowicka et al. 2016).

GPS data from the survey were prepared as in Sila-Nowicka et al. (2016). We segmented trajectories into movement and non-movement segments that corresponded to travel modes and stops (for more details about data segmentation and travel mode detection used for this paper see (Siła-Nowicka et al. 2016), for a general overview of the available methods see (Nguyen et al. 2020). We further identified the purposes of each trip by linking the GPS data to contextual

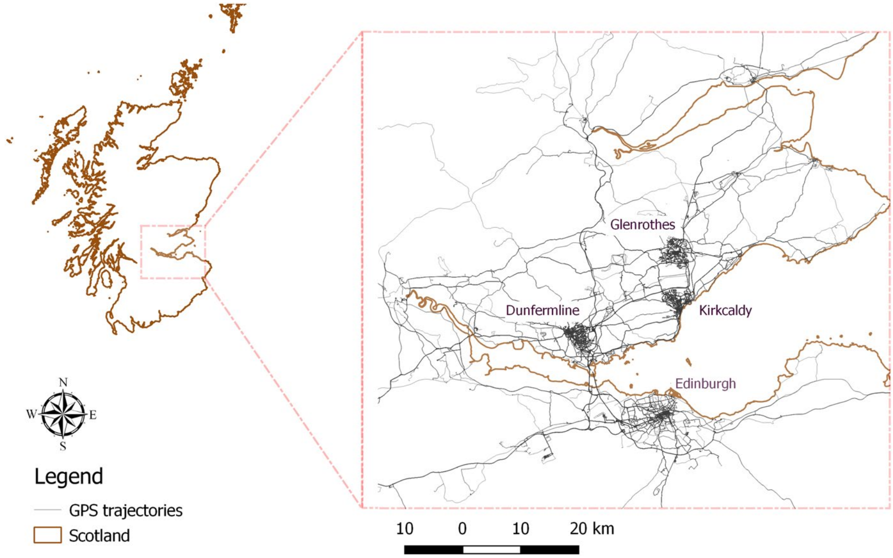

Fig. 2 Study area with GPS trajectories and three towns included in the study

information (Points of Interest data and public transport data from Ordnance Survey and OpenStreetMap). Specifically, we identified the locations of what Hummon and Oldenburg (1991) and Ahas et al. (2010a) term significant/anchor places/points (SP, i.e. places where an individual spends large proportions of time) and categorised these SPs according to the frequency of visitation and the amount of time spent in each location giving these two parameters equal weights (50%). To account for the frequency, we identified a ratio of visitations at a particular location to all the visited locations and assigned this value to the location. To account for the time spent in a location, we calculated the ratio of time spent in each of these locations to the total time spent in all the locations. With the maximum value of either of these parameters being one and the equal weights of 50%, we got a significance ranking ranging from zero to one. The most frequently visited place with the longest duration of stay for which the significance ranking was closest to one was considered to be home. The following places in this categorisation were named as SPs 1, 2, 3, and so on. We excluded from the dataset transportation and traffic-related stops. A person's home, together with their first three SPs, is the basis of our new activity space measure, the activity triangle. The time spent in the four initial SPs (home and SPs 1, 2, and 3) accounts on average for 90% of people's total time spent in places where people stop. Following Ahas's et al. (2010a; b) definition of significant aka anchor locations, an individual has to spend in such location minimum two hours within a week. This is the case only for the first three SPs in our case studies. Furthermore, time spent in the fourth most popular location (aside from home), SP4, averaged around 15 min daily in our three samples. This also corresponds to previous research by

Papandrea et al. (2013), and Vazquez-Prokopec (2013) who found that on average people have four significant locations.

4 Defining a new activity space measure

We define the activity triangle as a triangle whose centre of gravity is defined as the home location (H). From H, we draw three axes at 120 degrees and place the three SPs onto each of the three axes at their respective geographical distances from H. Figure 3a shows an example of an idealised triangle where the distances from H to each of the three are equal. In reality, this is not the case, and panel b) shows a more realistic activity triangle.

The new activity space measure A_{AS} is then defined as the area of the activity triangle. For the idealised situation in (Fig. 3a), this equals to:

$$A_{AS} = \frac{a^2\sqrt{3}}{4}, \tag{1}$$

where a is the side of the equilateral triangle and $\alpha = 120°$ and b is the distance between SP_i and home H.

For a general case, where distances from home H to SP_1, $SP2_2$ and SP_3 are e, f and g, respectively, we can calculate the area of the triangle SP_1-SP_2-SP_3 as:

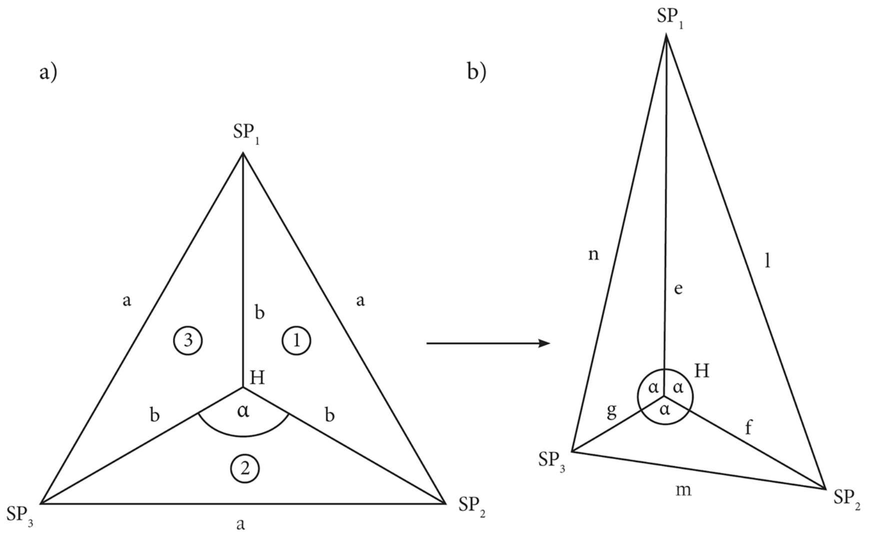

Fig. 3 Definition of the activity triangle. Panel **a** shows the case where the distance from H to each SP is the same and equals **b**, Panel **b** shows a transition to a more realistic case where distances between H and SPs 1–3 are not equal (marked with **e**, **f**, **g**)

$$A_{\mathrm{AS}} = \frac{e \times f \times \sin(\alpha)}{2} + \frac{f \times g \times \sin(\alpha)}{2} + \frac{g \times e \times \sin(\alpha)}{2}, \tag{2}$$

where $\alpha = 120°$.

While this measure is not fully spatial, as it does not describe the actual geographical extent of the individual's undertaken activities, it does allow the examination of the spatial dispersal of human movements across different distances.

We further describe the activity triangle by a measure of its compactness. We do not rely solely on the size of activity triangles, since activity triangles of equal areas may have very different shapes, thus presenting a different structure of the potential extent of human spatial behaviour (see Manaugh and El-Geneidy (2012) for types of compactness). Therefore, we introduce a second characteristic, the compactness C, so we can exploit both the shape and the area of the activity triangle to describe the activity space. Compactness C is defined as:

$$C = \frac{3\sqrt{3}}{\pi} \times \frac{A_{\mathrm{circle}}}{A_{\mathrm{AS}}}, \tag{3}$$

where A_{circle} is the area of an inscribed circle within the activity triangle and A_{AS} is the area of the activity triangle. The compactness C varies from zero to one, it equals zero for thin and long triangles and one for an equilateral triangle. To calculate the area of the inscribed circle in AS (Fig. 4), we first calculate its radius:

$$r = \sqrt{\frac{(p-m)(p-n)(p-l)}{p}}, \tag{4}$$

where p is half the length of the perimeter of the triangle and l, m and n are the lengths of the triangle sides. We get p as per this:

$$p = \frac{l+m+n}{2} \tag{5}$$

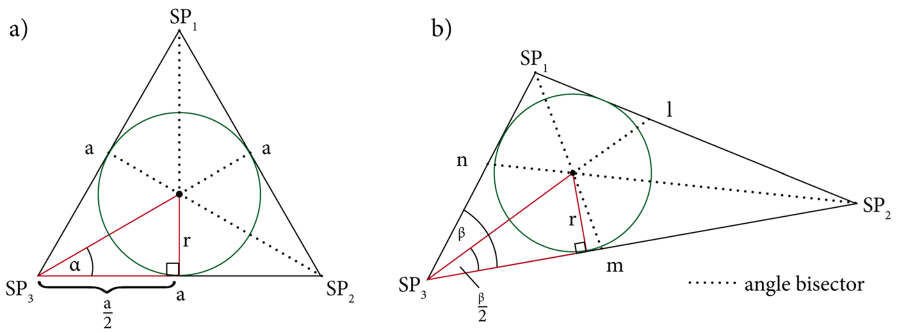

Fig. 4 An example of geometric construction of activity triangle with marked inscribed circle for **a** equilateral triangle; **b** activity triangle. The derivation of the ratio is shown under the circles

To obtain the side lengths l, m and n, we use the law of cosines that can be written as:

$$l^2 = e^2 + f^2 - 2ef\cos(\gamma), \tag{6}$$

where l is one of the side lengths of the activity triangle AS' and e and f are the distances from home to the two SPs that are adjacent to l, SP1 and SP2. The other two side lengths, m and n are calculated using the two respective adjacent SPs.

To investigate the extent of the spatial behaviour of an individual, we can now jointly consider the area and compactness of his/her activity triangle. If the area of the activity triangle is large and the compactness value is small that means that one of the significant places SP_i is further away from home than the other two. If the area of the activity space is large and compactness is close to one, then top three SPs are approximately equally far from the location of home. Table 2 and Fig. 5 show some simulated examples of how the area and compactness change with the shape of the activity triangle, that is, with the variation in distances of the significant places from home.

Small and compact triangles mean that an individual has top three of their significant locations within a compact area around his/her home location. Big, equilateral triangles indicate that top three significant locations of a particular individual are spread further from home. In a situation where two of the significant locations are close to home and a third much further away, the compactness decreases. Having one of the locations relatively close to home (1 km), one five or ten times further than the first one (5 or 10 km) and the last one up to twice as far as the second one (10 or 20 km) would result in the compactness levels of 0.595 and 0.626, respectively.

5 Application of our new measure to GPS data

We calculated activity triangles, their areas and compactness values for each of the 132 individuals in our data for whom we had age and gender information, 62 of which were from Dunfermline, 32 from Kirkcaldy and 38 from Glenrothes. Two further participants were identified as outliers and eliminated. They both had long flight

Table 2 Area (km^2) and compactness of activity triangles for different variations in the distances of $SP_{1\text{-}2\text{–}3}$ from home. Distances in km. Figure 5 shows these seven triangles

Example	Distance to SP1	Distance to SP2	Distance to SP3	Area	Compactness
1	1	1	1	1.30	0.999
2	1	1	3	3.03	0.787
3	1	3	3	6.50	0.876
4	1	10	10	51.96	0.732
5	1	1	10	9.09	0.363
6	0.1	1	10	4.81	0.213
7	1	3	10	18.62	0.575

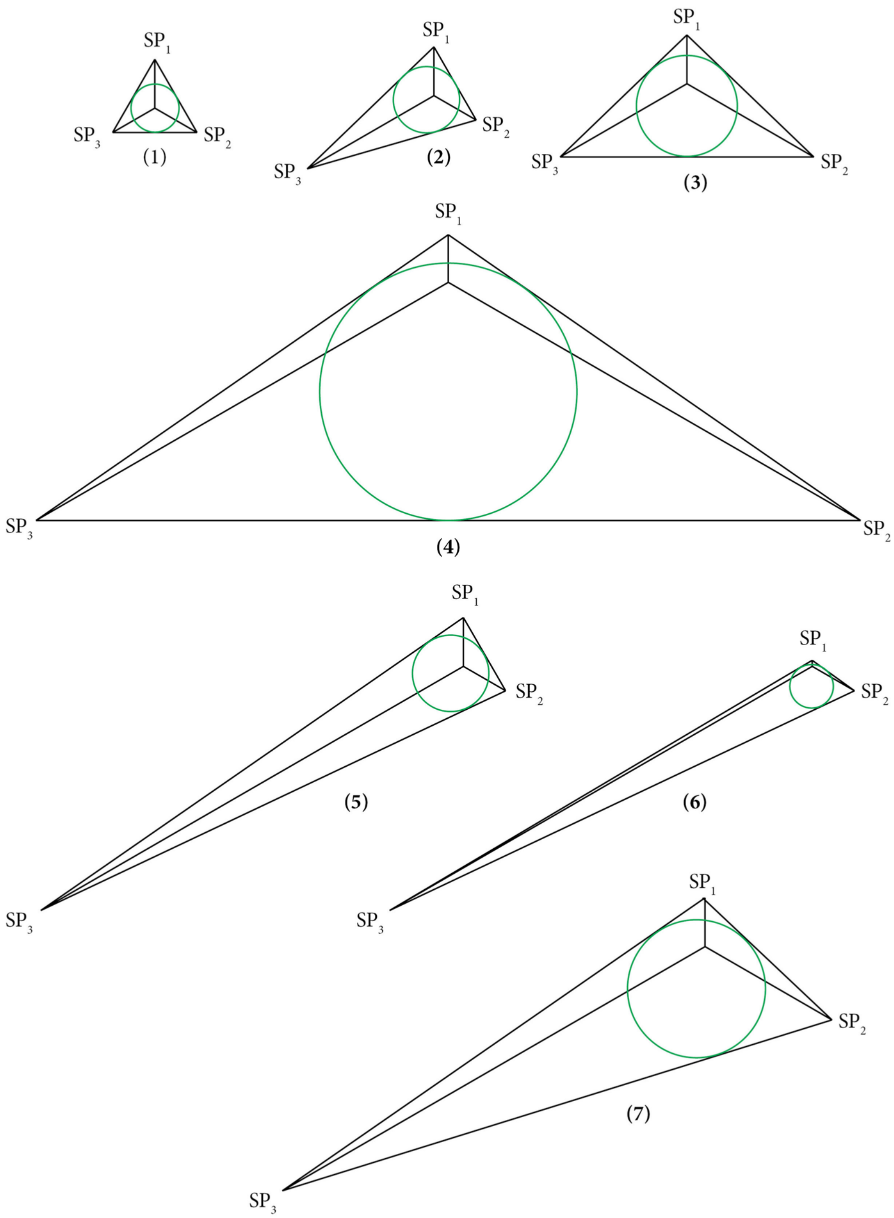

Fig. 5 Examples of activity triangles from Table 2

journeys to other countries which were not likely to be a part of normal weekly routines. Results are summarised in Table 3

The average areas and compactness levels varied between male and female participants across the study area. As the data were not normally distributed and

Table 3 Summary of area and compactness measures of activity triangles from real data

Area of activity triangle				Compactness of activity triangle			
Statistics	Male	Female	All	Statistic	Male	Female	All
Glenrothes				Glenrothes			
Participants with age information							
Sample	21	17	38				
Min	0.45	0.15	0.15	Min	0.083	0.156	0.083
Max	1086.65	1998.40	1998.40	Max	0.999	0.965	0.999
Mean	140.53	333.75	226.97	Mean	0.619	0.599	0.610
Median	30.05	93.70	56.50	Median	0.656	0.638	0.647
St Dev	300.21	533.23	425.24	St Dev	0.301	0.226	0.267
Dunfermline				Dunfermline			
Participants with age information							
Sample	40	22	62				
Min	1.65	0.48	0.48	Min	0.041	0.000	0.000
Max	5787.29	1323.14	5787.29	Max	0.999	0.999	0.999
Mean	538.34	158.80	403.66	Mean	0.642	0.564	0.614
Median	140.21	18.32	69.50	Median	0.712	0.638	0.666
St Dev	1185.30	308.25	982.31	St Dev	0.333	0.287	0.317
Kirkcaldy				Kirkcaldy			
Participants with age information							
Sample	20	10	30				
Min	0.09	0.74	0.09	Min	0.151	0.082	0.082
Max	501.17	563.42	563.42	Max	0.989	0.831	0.989
Mean	79.16	81.11	79.81	Mean	0.668	0.530	0.622
Median	12.80	6.49	8.53	Median	0.660	0.562	0.658
St Dev	129.27	178.29	144.16	St Dev	0.242	0.250	0.249

sample sizes were unequal and small, we tested the differences between distributions and medians using the Kolmogorov–Smirnov (KS) test and Kruskal–Wallis (KW) test, respectively. We ran two tests, as sometimes there are non-significant differences in means but significant differences in distributions. We only comment on significant differences and mark them as (KW) and/or (KS) where there is a significant difference ($p < 0.05$) on at least one of the tests. The median area of activity space for male participants was more than 1.5 times higher than for female participants ($A_{\text{Female}} = 31$ km^2; $A_{\text{Male}} = 55$ km^2), although the difference is not significant as there are considerable variations in the dimensions of the activity triangles between the three studied towns (KW, $p = 0.047$). The average compactness level of activity triangle for male participants was 15% higher than for female participants

($C_{Female} = 0.63$; $C_{Male} = 0.68$), indicating that males had their significant places grouped closer together (KW, $p = 0.027$; KS, $p = 0.044$).

There are significant differences between male and female activity triangle areas in the three studied towns. Median areas of activity triangles, for both male and female participants, are the largest in Dunfermline ($A_{Female} = 18$ km^2; $A_{Male} = 140$ km^2); and the smallest for Kirkcaldy ($A_{Female} = 6$ km^2; $A_{Male} = 13$ km^2). This vastly significant difference probably is a result of commuting patterns of participants from these two towns (KW, $p = 0.037$; KS, $p = 0.029$) where Dunfermline is known as much more of a commuter town given in its close proximity to the capital city Edinburgh (Fig. 2). Areas of activity triangles from people in Kirkcaldy were also significantly different from the ones in Glenrothes ($A_{Female} = 94$ km^2; $A_{Male} = 30$ km^2), (KW, $p = 0.026$; KS, $p = 0.032$). The participants in Kirkcaldy tended to have much shorter commuting trips affecting the size of the activity triangle. One possible explanation for these differences can be the actual commuting patterns observed in Scottish Census from 2010. The male working population from Dunfermline commutes mainly to Edinburgh; the population from Glenrothes has a high percentage of people working in Glenrothes, Kirkcaldy as well as Dundee and Edinburgh, whereas people from Kirkcaldy seem to work much more locally, mainly in Kirkcaldy and nearby Glenrothes (Census 2011). The average compactness levels for male and female participants in all three towns are not significantly different. This means that in all three towns females tend to have at least one of their significant places situated relatively further away than the other two (Fig. 4.7). With the average compactness across all three towns equal to $C = 0.61$ across all the participants in the study area, we can assume that the average shape of the activity triangle is between shapes of triangles from Fig. 4.7 and Fig. 4.4 having one of the locations relatively close to home and the other two further away.

Even though on average males seem to travel further to work than females (15 km vs. 11 km according to Barker and Connolly (2006)), the latter often have bigger activity spaces and their sizes decrease with age (Fig. 6) (KW, $p = 0.026$) what corresponds to the results in Schönfelder and Axhausen (2003). This could potentially

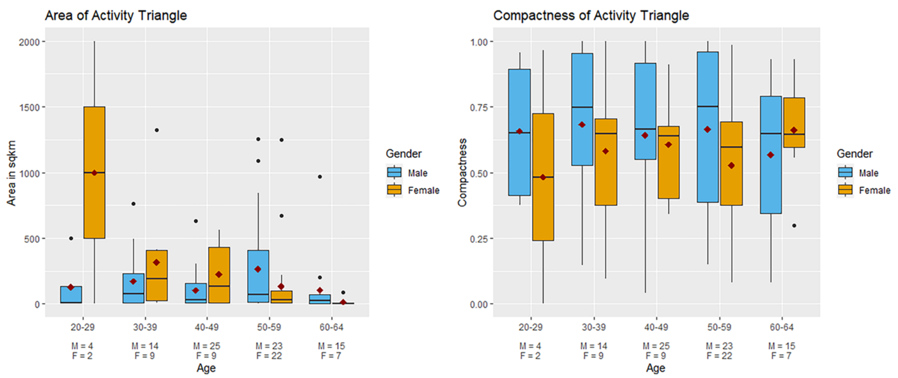

Fig. 6 Box plots of area and compactness for activity triangles per gender and age in the study area. Red diamond corresponds to a mean value

be explained by unequal gender roles, with females more likely to be responsible for escorting children to school and after-school activities (Motte-Baumvol et al. 2017). For female participants ($n=49$), the level of compactness is lower than that for males ($n=81$) (KW, $p<0.05$; KS, $p<0.05$). There are also significant differences across all the age groups reaching minimum difference for the oldest group in the sample (KW, $p<0.05$ for all the age groups apart from 20–29 and 60–64; KS, $p<0.05$ for all the age groups apart from 40–49 and 60–64). The differences between sizes and compactness levels of activity spaces for age groups (20–29; 30–39; 40–49; 50–59 and more than 60) for males and females are shown in Fig. 6.

The size of activity spaces increases with age for participants from Dunfermline (until 50 years old) and decreases with age for participants in Glenrothes and Kirkcaldy. It seems that Dunfermline serves as a commuter town for most of age groups of people working in Edinburgh; however, people over 40 years old are less likely to consider commuting to Edinburgh from Kirkcaldy or Glenrothes (Barker and Connolly 2006). In all three cases, the activity space sizes are on average the smallest for individuals over 60 years old (Fig. 7) (KW, $p<0.001$; KS, $p=0.016$). This conforms to common belief that people closer to their retirement or already retired tend to spend more time locally and travel shorter distances (Lido et al. 2016; Kim et al. 2020).

There are significant differences between the compactness of activity triangles for people of different ages in the studied towns (Dunfermline: KW, $p<0.001$; Glenrothes: KW, $p<0.001$; Kirkcaldy: KW, $p>0.1$). Similar to the measures of size, the levels of compactness of activity triangles for Kirkcaldy and Glenrothes are the smallest for the oldest participants in the study (Fig. 7). It is in contrast to what can be seen in Dunfermline where the activity triangles of the oldest participants are actually the most compact. In Dunfermline, compactness levels increase with age and decrease with age in the other two towns. This may correspond to commuting patterns in these three towns as well as the availability of different social venues such as restaurants, cafes and social clubs where individuals may

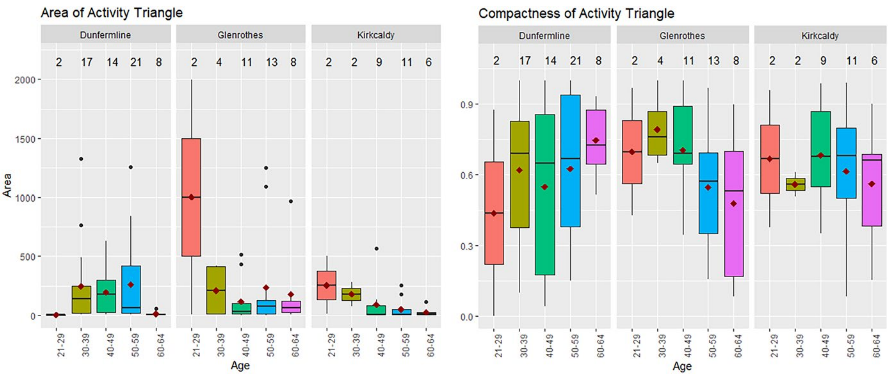

Fig. 7 Box plots of area and compactness for activity triangles per age group in each of the three towns. Red diamond corresponds to the mean value of the measured parameter. Numbers over the boxplots correspond to the sizes of groups

want to spend their free time (Hummon and Oldenburg 1991; Finlay et al. 2019). If these venues are available near to home/work locations and individuals do not travel further to one of these "third places", the compactness levels would be closer to one.

We further investigated the influence of gender on activity space delimitation. Figure 8 shows the average activity triangle calculated for each gender and

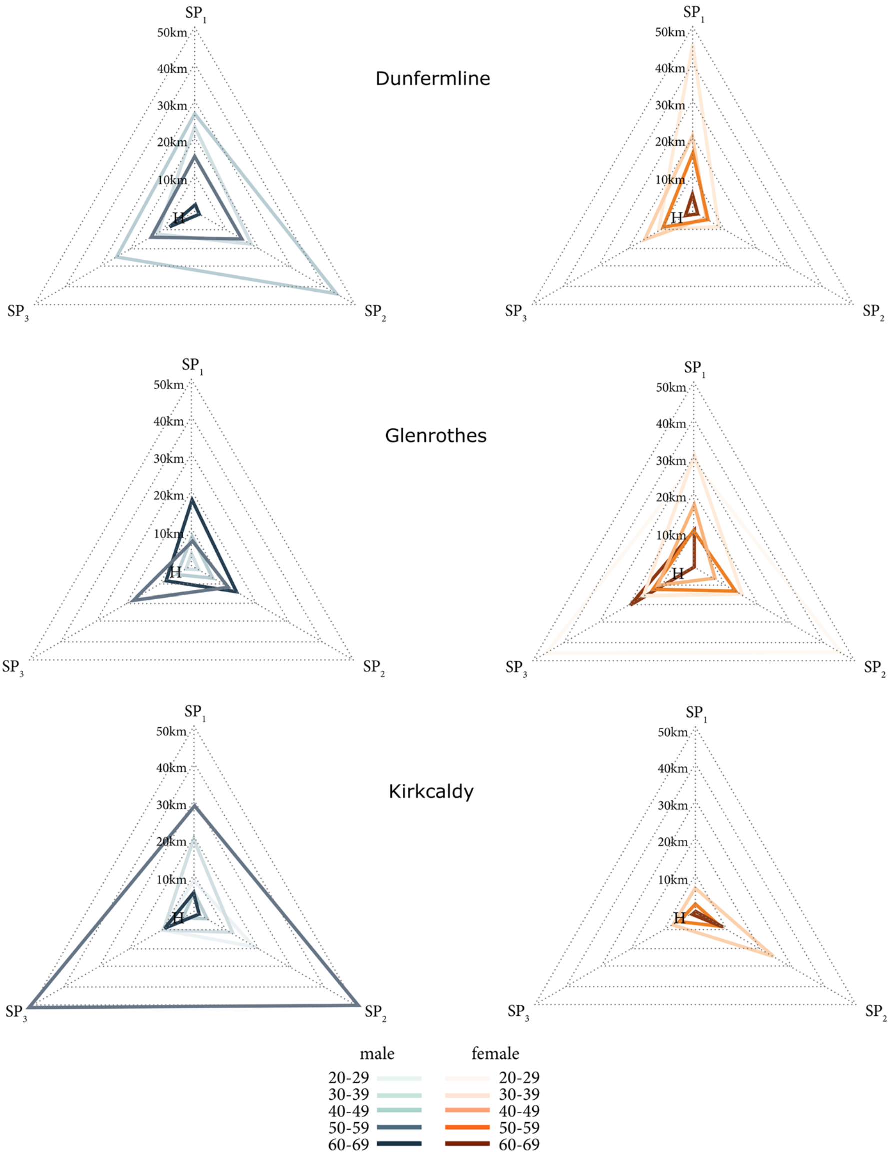

Fig. 8 Aggregated activity triangles for each gender/age category in the three studied towns

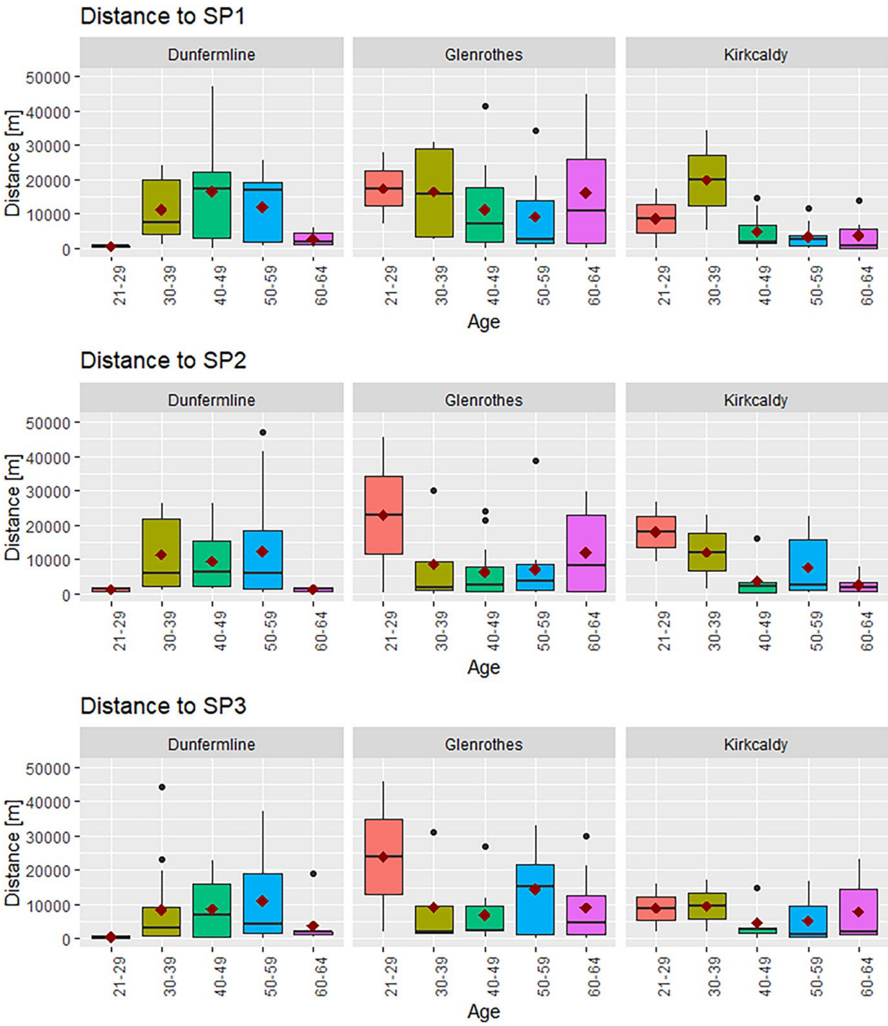

Fig. 9 Distribution of distances to significant locations in different age groups for participants in the three studied cities: Dunfermline, Glenrothes and Kirkcaldy. Red diamond corresponds to the mean value of the measured parameter

age group. In Dunfermline, the average extent of activity spaces for males and females is similar, whereas in Glenrothes and Kirkcaldy, the differences between the genders are more apparent. Females tend to travel further to their SP_3 which may be related to escorting children to after-school social events. There are significant differences in the sizes of activity spaces between Dunfermline and Kirkcaldy (KS, $p=0.029$) and Glenrothes and Kirkcaldy (KS, $p=0.032$) showing that Kirkcaldy has much more local movement patterns than the other two towns.

Table 4 Qualitative comparison between activity spaces

Q1	Can activity space be created using all types of movement data (GPS, CDRs, Travel Surveys)?
Q2	Does it show the spatial extent of spatial behaviour?
Q3	Does it overestimate the size of space that individual uses in daily routines?
Q4	Does it show unrealistic potential areas used by individuals?
Q5	Does it help to describe spatial behaviour?
Q6	Does it preserve privacy?
Q7	Can it detect relationships between locations?
Q8	Does combining it with other measures improve the understanding of spatial behaviour?
Q9	Does ambiguity in interpretation decrease when Activity Triangle and this measure are combined?
Q10	When using GPS data, does it require pre-processing/semantic enrichment?
Q11	Does it provide semantic information?

Activity space

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11
MCP	YES	YES	YES	YES	YES	YES /NO*	NO	YES **	YES	NO	NO
Home-Work Ellipse	YES	YES	YES /NO#	YES	YES	YES/ NO*	NO	YES	YES	YES	YES
SDE	YES	YES	YES	YES	YES	YES /NO*	NO	YES **	YES	NO	NO
Weighted SDE	YES	YES	YES	YES	YES	YES /NO*	NO	YES **	YES	YES	NO
PPA—road network-based	YES /NO###	YES	YES	NO	YES	NO	NO	YES	YES	NO ***	NO
Activity triangle	YES	YES ##	NO ##	NO ##	YES	YES	YES	YES	N/A	YES	YES

*Depends on the accuracy and the size the AS

**Combining it with highly correlated ellipse-based/MCP measures is not advisable

***Map matching would be beneficial

#Unlikely but it would depend on the locations of Home and Workplaces

##The size is not related to geographical extent

###The route between points must be simulated (e.g. shortest path)

Our findings suggest that there is a difference between the compactness levels among men (($n=81$) and women ($n=49$) (KW, $p=0.027$; KS, $p=0.044$). Men tend to have their major locations clustered in similar distances away from home locations, whereas women tend to have at least one of the significant locations located further away from home. The pattern is visible for all age groups with the differences between men and women decreasing with age (Figs. 6, 7 and 8).

To further investigate the mobility behaviour of participants we looked for relationships between significant locations, distances to them as well as place of origin and socio-demographic characteristics. As indicated in Fig. 9, the travelled distances to significant locations $SP_{1\text{-}3}$ in Dunfermline show an opposite trend to

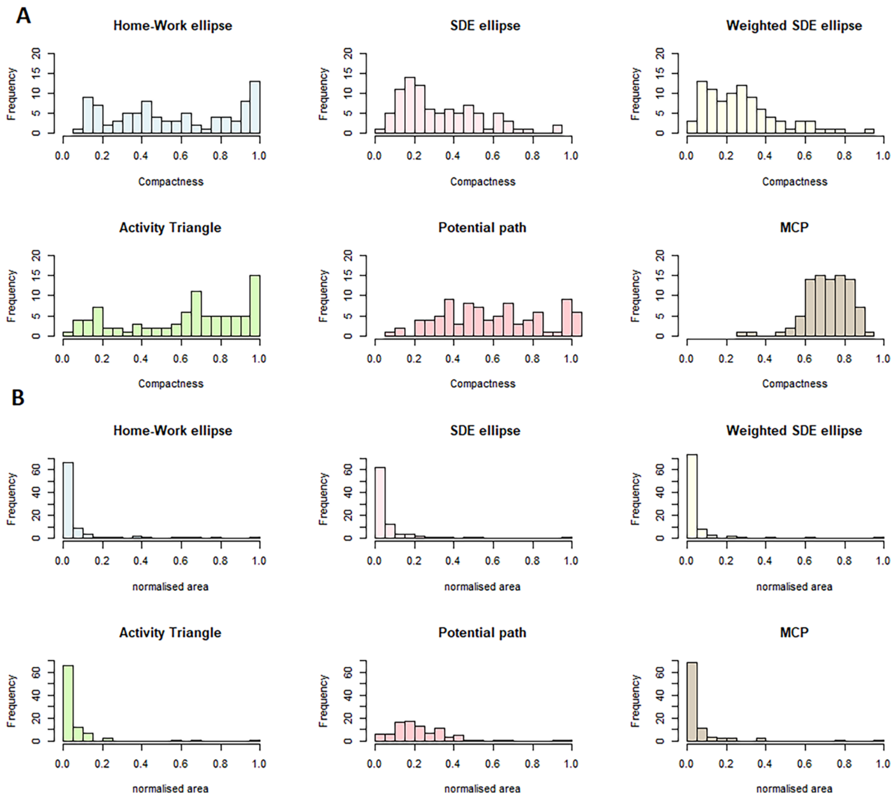

Fig. 10 Distribution of compactness levels and sizes of activity spaces for the users in the three study areas

what can be seen for the participants from Glenrothes. The travelled distances to top three significant locations tend to increase with age in Dunfermline for people between 30 and 60 years old and then decrease to reach the minimum values for people over 60 years old. In Glenrothes, the data indicate the opposite trend with the highest values for older individuals. Individuals from Kirkcaldy have on average the shortest distances to top three SPs, and they tend to decrease with age of individuals.

6 Comparison of methods

This section provides a qualitative and quantitative comparison between six activity space measures and a visual example explaining the differences between AT and MCP measures. To qualitatively describe the differences between the studied activity spaces, we set 11 questions on the characteristics of each method to help

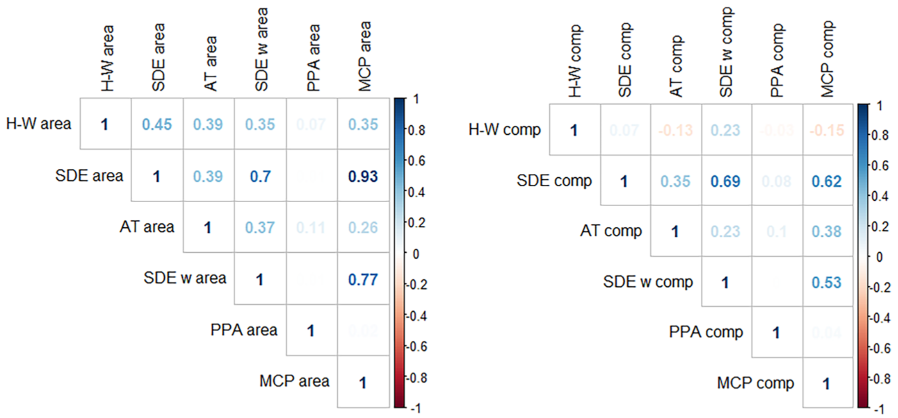

Fig. 11 Pearson's correlation matrix for **a** sizes and **b** compactness levels of activity spaces

establish their relative advantages and disadvantages. Questions, along with the characteristics, are shown in Table 4.

Using raw, unprocessed movement data is only feasible for calculating MCP and SDE. All the other methods require a certain level of pre-processing to identify either significant locations or at least time and visitation frequency. Time-weighted SDE shows the importance of places that are visited for a long time, and frequency-based weighting of SDE would only work if the data were heavily pre-processed to calculate actual returns rather than all the points (Sherman et al. 2005). Thus, this would make AT similarly complicated and as computationally heavy as other properly calculated methods.

All studied activity spaces can be created using multiple data sources (GPS, CDRs, survey-based travel diaries). Most visualisations of activity spaces can be used to identify individuals, especially if these spaces are small and constrained. Using significant locations only can cause privacy concerns for all but AT measures. All activity spaces tend to overestimate the extent of spatial behaviour, limiting potential uses. AT does not do that as it is not a geographic measure. Regardless, the distribution of sizes of all activity spaces but PPA are similar, meaning their measures capture similar patterns (Figs. 10 and 11).

The distributions of the normalised sizes for all activity spaces but PPA show similar patterns. Interesting differences are visible in the compactness levels (Fig. 10). SDE (1 STD/2STD) are more compact than MCP, which in our case, uses all the data available. The Home-Work ellipse shows a wide range of compactness values as adding semantics to the data may allow a better approximation of activity space. These differences result from how these metrics are calculated and possibly the effects of urban infrastructure.

Following Tao's et al. (2020) way of comparing activity spaces, we used Pearson's correlation to verify which metrics capture similar dimensions (Fig. 11). It can be clearly seen that areas/sizes of H-W ellipse, SDE, SDE weighted, and MCP are strongly and positively correlated, thus explaining similar dimensions. AT level of correlation for size is also positive but significantly lower than the already mentioned metrics. PPA, as it is a buffer along the travelled road network, is not correlated with other measures. Compactness levels show more interesting patterns where SDE, SDE weighted, and PPA are similar, and other metrics (including our AT) capture different dimensions of individual behaviour.

Depending on the resolution and the amount of data (GPS data vs travel survey information), the resultant activity spaces will have different sizes and shapes. To show the potential differences or similarities between methods, we have calculated three different activity spaces using data from an individual user (the same user as in Fig. 1): MCP (perimeter 93 km, area—393 km^2 and fullness/compactness 0.571), MCP_SP, MCP using only SPs (perimeter = 74 km, area 19 km^2, fullness/compactness 0.027), and AT, our activity triangle built using only the significant locations (perimeter 75 km, area 649 km^2 and compactness 0.688). MCP fences all the GPS data and is marked as a red polygon in Fig. 10. MCP_SP (black in Fig. 12) is very narrow and long as the significant locations of this individual are far away from each other, which is not evident from just looking at MCP. Unlike the AT, by looking at MCP or MCP_SP or their characteristics (size and compactness), we cannot identify which are the areas where a person would spend the most amount of time. Through AT (green in Fig. 12), we can estimate that at least two out of three locations are far away from home, so they are probably grouped in one of the ends of the narrow MCP_SP. Without knowing how far significant locations are from each other, we could equally likely assume that the AT could look like the one marked with a blue dashed line (perimeter = 53 km, area 42 km^2, fullness/compactness 0.224). As

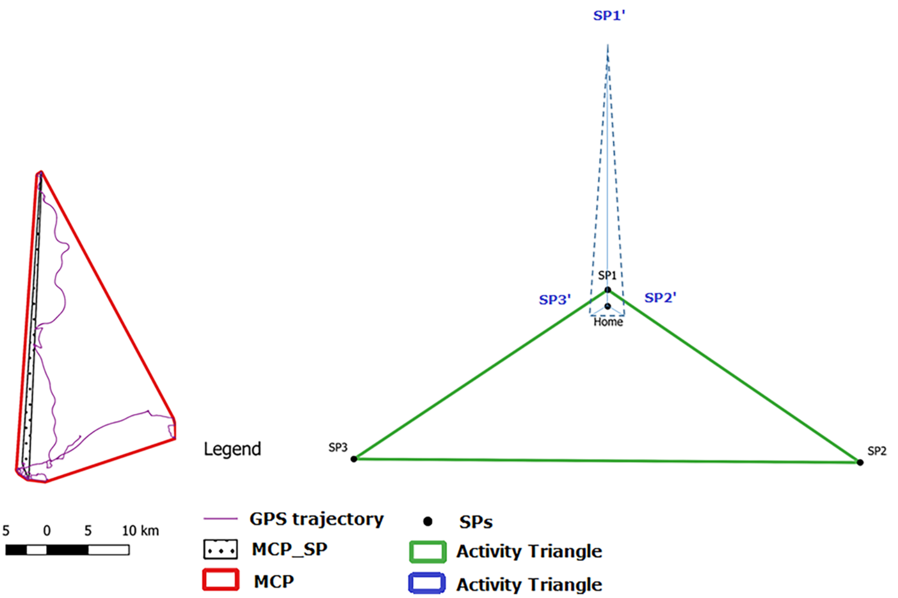

Fig. 12 Comparison between minimum convex polygon (MCP), MCP significant places/points (MCP_SP), and activity triangle (AT)

the effect of number of locations (all versus significant only) used to create activity spaces (MCP vs MCP_SP) on their size and shape vary, the conclusions using these activity spaces to understand people's accessibility or segregation levels would be different. The differences between MCP and MCP_SP is massive because of a high number of GPS data points and all the driving routes being accounted for in MCP and not MCP_SP.

There is no single best method for all purposes, and the results from each method vary depending on the particular task. Looking at multiple measures simultaneously and visualising them can potentially bring more insight into a studied phenomenon (Hirsch et al. 2014; Patterson and Farber 2015). Using a combination of MCP and our activity triangle can provide us with more detailed information about people's trips and movement behaviour than using a single measure alone. There can be a huge variation in the sizes and compactness of different activity spaces. These differences can help us understand whether people tend to socialise or interact with services in places closer or farther away from their homes. Taking Dunfermline as an example, we see that it tends to have the lowest average compactness for MCP, which makes sense as it is a commuter town for Edinburgh—people travel further to work, which elongates their activity spaces. Having higher compactness for activity triangles means that these people would work in Edinburgh and have their other activities closer to there. This relationship could not be spotted with just one of the methods. Our method is not geographic, but as such, it will not breach privacy levels and will not overestimate the size of people's activities. Unlike other measures, AT provides certain semantic information about the significant locations of an individual.

7 Conclusions

The recent availability of high quality spatio-temporal movement data brings opportunities to develop new methods for understanding human mobility. The latter is important for urban and transportation planners, policy-makers, epidemiologists, and other health professional among others. In this paper, we define a new activity space measure which is applied to a data set of semantically enriched GPS data and used to demonstrate the possibilities of these measures for comparing spatial behaviour between different groups of individuals. Our method links the distances travelled to different places to the observation of whether people group their activities or not, a connection that is not possible using other methods for activity space measurement.

Looking into the distances between people's daily activities in conjunction with socio-demographic and health-related data can reveal new insights about commuting times/distances that can be associated with a lack of health-related activities (Christian 2012). The distances people travel between routine locations (work, home) have a high impact on their well-being, mental and physical health, and job satisfaction. Gender and the type of occupation influences the distances people travel (Shuttleworth and Gould 2010) with gender having a strong effect on chronological binding of locations also known as space–time fixity (Shen et al. 2015). Studying these relationships is crucial for understanding modern society and people's behaviours. We believe that with a simple and computationally undemanding measure, we can explore the links between distances people travel in their individual daily routines the possible effects on their well-being. Size, shape, and a visual representation of the activity triangle can help understand the differences in movement behaviour among different population groups and across different locations.

Although the application described here uses semantically enriched GPS data, it could also be applied to data on activities derived from standard travel surveys. Such surveys usually provide post-code or small census unit-level information about the locations of places where people start and end their journeys. Depending on the length of the travel survey (one day/week/month), these locations could be used to designate significant places and to calculate either Euclidean or road network distance from them to a home location.

The existing activity space research has several shortcomings. Ellipses and minimum convex polygons generalise patterns of activities, and their size is overestimated and therefore does not accurately represent individuals' behaviour and use of space. Both ellipses and MCPs cannot be constructed if all the locations in an individual's routine form a straight line. This peculiar but not uncommon scenario does not affect the activity triangle. Activity spaces tend not to have a temporal dimension and therefore are only used to describe the spatial extent of space–time prisms (Hägerstrand 1970). By incorporating the significance of locations and distances to them, our activity triangle partially integrates temporal dimension into an activity space. While the proposed method of defining and displaying activity spaces appears to have benefits over existing techniques, further research could be beneficial on several issues. First, in the example given here, we used seven days of GPS data per individual which may not be enough to determine representative significant locations in the daily routines of individuals. Some recent studies, for example, suggest at least two if not three weeks of data are required to establish people's routines (Pappalardo et al. 2015; Smolak et al. 2020). Also, the data can be incomplete, and the results can be inaccurate (Sila-Nowicka et al. 2016), not to mention that the results from small GPS-based studies are not representative and should not be generalised.

Secondly, we identified and categorised significant places according to the frequency of occurrence and the amount of time spent in each location. There are other definitions of significant places which could be employed, although whatever definition is used, there will be some amount of subjectivity. Although this does not subtract from the methodology described here, the definition of what constitutes a significant place does need attention.

Thirdly, the activity measure presented above is spatial but not geographical. It aims to measure aspects of human behaviour that cannot be measured by other activity space measures. For example, using minimum convex polygons, ellipses, KDE-based methods or network-based measures, the potential used space can be estimated but the relationships between the places visited are hidden. These other methods could also be used to interpret the accessibility of services within an activity space which currently cannot be done with activity triangles. However, activity triangles allow us to understand whether an individual tends to locate his/her significant activities near the home or whether these locations are further away. Our method could be used not only for identifying the distance relationship between significant locations but also to analyse shopping behaviour, such as how particular individuals choose their regular supermarkets. Because of the high temporal resolution of movement data (five second intervals), the shapes and sizes of created activity spaces can vary based on the length of a movement trajectory from which the significant locations are extracted. This would allow studying seasonality or temporal patterns of human mobility.

Fourthly, quite often, activity spaces are used in conjunction with socio-demographical information in order to understand how different factors affect human mobility behaviours and at the same time the size and possibly compactness of the activity space. It has been shown that with a set of socio-demographic and economic characteristics of individuals, we could identify the potential for social exclusion (Schönfelder and Axhausen 2003; Šimon et al. 2019) or spatial inequalities in accessibility to health facilities (Sherman et al. 2005). Our study had limited socio-demographical information available but adding more details about participants would enrich our evaluation of how the proposed measure can help to understand spatial behaviour and the relationships of different groups with the built and natural environment.

To summarise, the activity triangle described here represents a new analytical tool for understanding mobility patterns. This simple method has a potential to be used across disciplines and answer a number of questions related to human mobility.

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Availability of data and material Data transparency—GPS movement data cannot be shared.

Code availability Software application or custom code.

Declarations

Conflict of interest The authors declare no conflict of interest.

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