Profiling and visualizing activity spaces of urban utility cyclists

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1. Introduction and Background

Recent literature concludes that there is a likelihood of activity-space approach to physical-activity analysis receiving much attention in the developed world (Schonfelder and Axhausen, 2010). Recent call for further research in detection and representation of activity spaces from portable GPS trackers, within the context of mobility pattern research is therefore timely (Thierry et al, 2013). However, little is known about the analysis of movement data in an explicit context and even less on the visualisation of actual urban cycling behaviours in available literature (Andrienko and Andrienko, 2013); particularly, when it comes to our understanding of individual level cycling behaviours in the British geographical context (Goodman, 2014). This is partly due to the lack of spatio-temporal information needed as input, but also due to the limited diffusion of innovative approaches for producing visualisation that add to the existing body of knowledge. *Context* is a vague and even versatile term in Visual Analytics (VA) since VA itself is quite broad. This paper therefore follows a view on conceptualization of context which makes the assumption that context is based on a fixed set of pre-determined descriptively well-defined terms used for processing and integrating information (Tomaszewski and A. M. Maceachren, 2010). This paper analyses, visualizes and explains activity spaces of actual movement behaviours of urban cyclists using a new dataset collected around Newcastle upon Tyne which is the urban core of the Tyneside conurbation in North East England. Analytical frameworks are drawn from visual analytics and Local Moran I spatial statistics in understanding urban cycling behaviour together with stationary and motile activity spaces concepts are used to understand urban cycling behaviours in both space and time. These concepts were operationalised using already established and publicly available area boundaries from the UK electoral Ward and the Census Output Areas (OA) geographies.

From a Space-Time Cube (STC) based visualisation perspective, several questions have been raised about how complex data can be visualized in STC. To enable meaningful visualizations, the approach taken in this paper draws on the visualisation approach suggested by Kapler and Wright (2004) which provides several ways of generating graphs from spatio-temporal data. Their tools have been developed as commercial software called “GeoTime” which is used throughout this paper for the visualization of space-time data. Other related software exists but is not easily accessible or usable, except mostly used by the main developers and close collaborators as technical support and documentation is not easily available. Andrienko and Andrienko (2013) provide examples of how CommonGIS could be used to visualize spatio-temporal movement data such as GPS trajectories of about 17,241 cars collected during one week in Italy. However, very little is known about the use of STC in visualizing movement data of cyclists. Because of the spatio-temporal characteristics of the

STC, it is possible to examine, for example, the peak time estimates of an event along with its spatial orientation. VA can provide a conceptual framework for the analysis and visualisation.

2. Data and Methods

This paper, therefore, draws on two aspects of space-time analysis. First, Local Moran's I spatial statistics are used to address distribution of cycling uptake and variation of cycling patterns in space. Secondly, activity space and space-time concepts are utilized to perform spatio-temporal analysis of cyclists GPS tracks. Four datasets are used in this paper:

- Cycle trips from the primary data collected in this study;
- The 2011 Census Output Areas (OAs);
- The 2012 electoral ward administrative boundaries from ONS; and,
- All modes of transport from the utility cyclists sampled in this study.

The first dataset comprised of only the cycle trips extracted. The second dataset was the 2011 Census OAs, the lowest official geographical unit in the UK, built from clusters of postcodes and designed to preserve confidentiality (ONS, 2013). Despite the original use of OA areas for census statistics, it also provides sound bases for researchers to undertake low level data analysis without giving away sensitive individual information. For example, Daniel and Bright (2011) used the first wave of the Wealth and Assets Survey together with OA areas to provide an in-depth understanding of the geographical distribution of wealth and its related components. Areas exhibiting common demographic and socio–economic characteristics, from relatively high to low levels of aggregation while overcoming the disclose problem, were mapped, graphed and tabulated. Daniel and Bright (2011) concluded that OA-based analysis further enhances our understanding of geographical trends. The 2012 electoral ward administrative boundaries from ONS covering the study area were the third dataset. Unlike the OAs, electoral wards are recognized as a spatial unit used for electoral purposes of local government councilors in districts and unitary authorities (ONS, 2013). The use of such geographical units for cycling research has been employed elsewhere in a Bicycle Study in New Zealand where addresses of participants were aggregated into a mesh-block (Tin Tin et al, 2010). The fourth dataset comprised all modes of transport taken by the tracked cyclists (i.e. bike, car etc.).

The concept of activity-space describes the actual or observed or revealed use of space (Schonfelder and Axhausen, 2010) and is deemed appropriate here for addressing movement behaviour of cyclists. Terms such as *stationary activity* are used to represent stops in movement or non-vigorous activity around stops in space and time. Horner et al (2012) used the term to explore un-locatable activity locations derived from travel surveys and examines individual time budget allocated to travel and stationary activity, while Miller (2007) used it to illustrate an analytical definition of the space-time prism. In the current research, the term *stationary activity* is used to explore and quantify where people stop or move at a low speed in their cycling trips. The term *motile activity* is borrowed from biological science research which refers to the ability to move whilst energy is spent in the movement process (Davis et al, 2011). This is taken as a description of cycling as an active transport mode, where active transport is a form of travel involving active human muscle during the journey (Cole et al, 2010). Although, it was possible to manually (which is time demanding) extract all stops for cycling journeys only, using the detailed travel diary, we utilized time constraints with a clustering method for the significantly low speed detections within the dataset. Here, significantly low speed clusters constituted Stationary Activity Space (SAS) and significantly high speed clusters constituted Motile Activity Space (MAS). Figure 1 shows how stationary activity space (SAS) and potential motile activity space (MAS) are conceptualized together with boundaries.

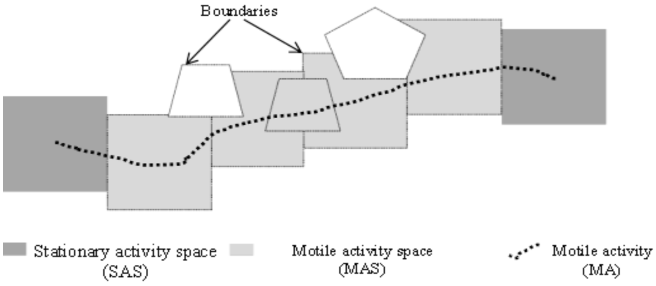

Figure 1. Conceptual diagram of stationary and motile activity spaces based on boundaries

The spatial information from activities performed by the participants and derived from the GPS trajectories were used to identify the activity spaces. The departure and arrival points of all 79 cyclists derived from the GPS traces were used as an input to ESRI ArcGIS 10.0 software, where both departure and arrival maps were generated. This way, the computed aggregate values for each area (e.g. OA) were represented on the generated map as characteristics of that area, following the example of Andrienko et al (2008). Figure 2 shows the general structure of analysis adopted here for analysing both the MAS and the SAS of the participants, alongside the characteristics of cycling flows.

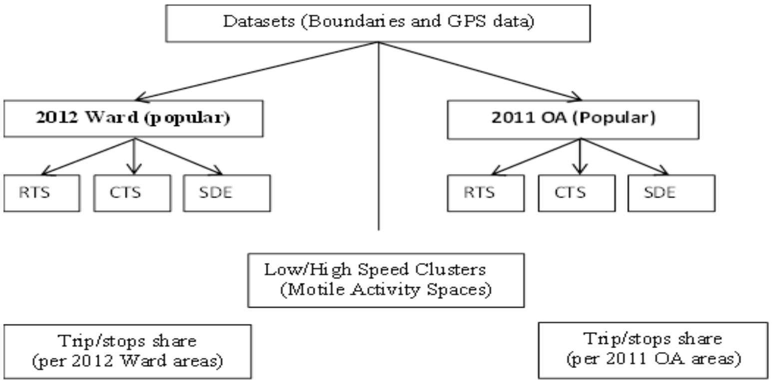

Figure 2. Overall presentation structure for SAS, MAS analysis

3. Analysis and Results

3.1 Exploratory analysis

Figure 3 shows a map of *departures* (origins) for cycling flows from the sample, based on OAs from the 2011 census and the 2012 electoral administrative wards. For presentation purposes, both the ward and the OA layers have been superimposed. From the viewpoint of electoral wards shown in this figure, the most frequented departure spaces fall within Westgate ward and the second most frequented ward is South Jesmond. From the perspective of OAs, the most frequented OA was in South Jesmond ward, with the second most frequented OA in Westgate ward. These descriptive findings show how using at least two spatially configured activity spaces could give clues as to where strategic investment of cycling could be directed.

Figure 4 shows a map of *arrivals* (destinations) for cycling flows from the sample based on the OAs from 2011 census and the 2012 ward areas. The two most frequented electoral wards for arrivals were identified as Westgate followed by South Jesmond. These findings make it clear that both Westgate and South Jesmond areas could serve as important places for the consideration of secure infrastructure for storing bicycles, for example, secure cycle parking. For the more detailed geography, the most frequented OA, fell in South Jesmond ward with the second most frequented OA in Westgate ward. In other words, the departure and arrival trends are very similar.

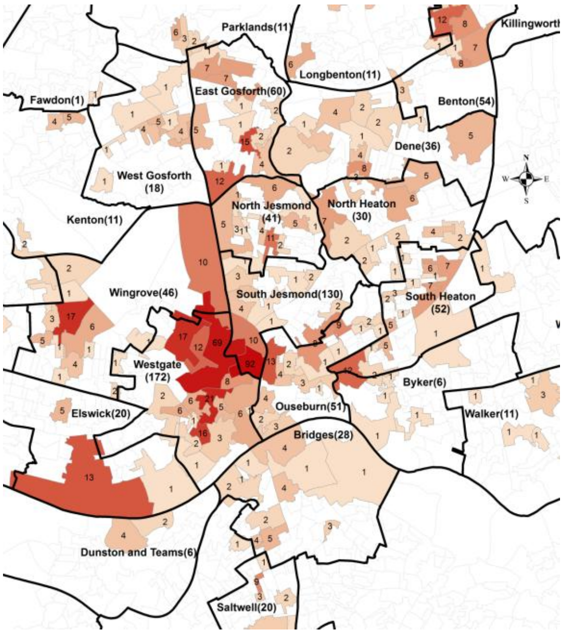

Figure 3. Map of *Departures* for actual cycling flows for Census OAs (Wards also shown)

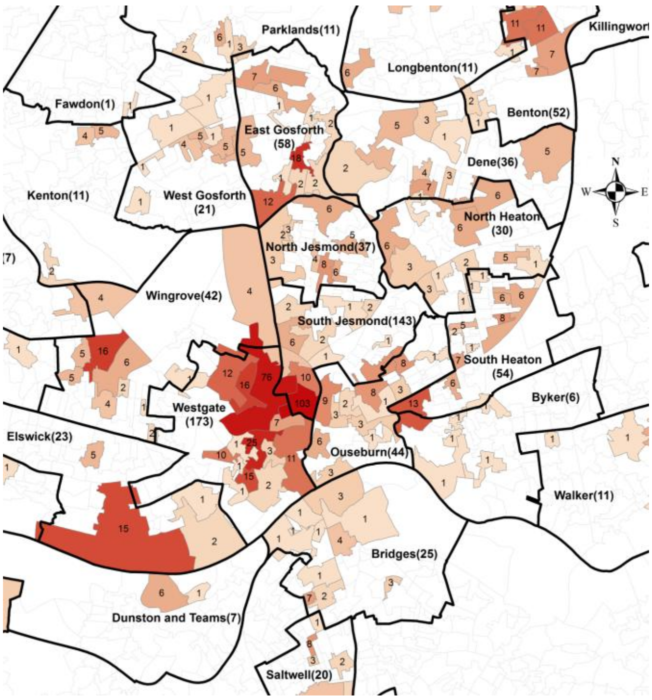

Figure 4. Map of *Arrivals* for actual cycling flows for Census OAs (Wards also shown)

The next step is to visualize stationary activities (i.e. departures and arrivals) within the most popular and frequented stationary activity spaces (already identified as the Westgate ward) together with the most popular OA using both RTS and CTS approaches. Figure 5 shows the realistic time status of arrivals' stationary activity spaces. This graphical representation follows visualisation approaches implemented using the GeoTime software (Kapler and Wright, 2004) within a Space Time Cube framework (Kristensson et al, 2009). All the stationary activities were grouped into: work related, work, non-food shopping, food shopping, home and other (e.g. visits). The colour scheme for the activities was chosen as follows. Grey was used for work related activities; Black for work activities; and Cyan for other activities. Blue and light-blue were used for food shopping and non-food shopping activities respectively, while the home activity was colour coded as green. The two-dimensional graph showing the Westgate boundary ward in the graph provides the spatial dimension to the temporal dimensional space. The rough rings around each grouped activity indicate the temporal stationary activity space (TSAS) of those activities. TSAS is not necessarily the same as the spatial stationary activity space since the timing of activity dictates the structure whereas spatial SAS denotes a two dimensional Euclidean space without any consideration to timings of activities. RTS and CTS of TSAS give cues to the extent of freedom an individual has and provide the limited space available to the freedom of movement. Thus, we are able to tell how cyclists share their time between mandatory activities and more time-flexible activities. For example, focusing on the *work* and *work related* activities suggests that the sampled cyclists did cycle to work throughout October and November with slight shift of work related cycling towards November. In addition, commuting by bike tends to generally mix with other cycling destinations, such as visiting a friend. Finally, food shopping activities by bike seem to be more constrained in space and time, but appear to be not so popular in this ward area.

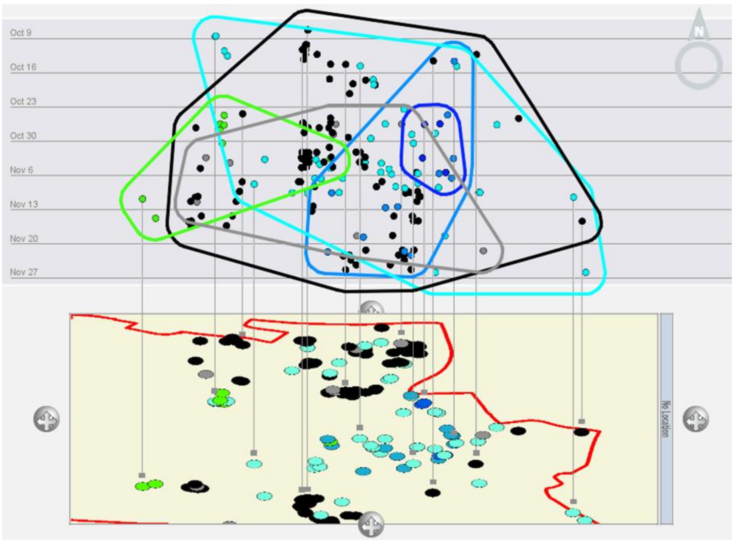

Figure 5. RTS for arrivals by purpose in most popular SAS (n=173)

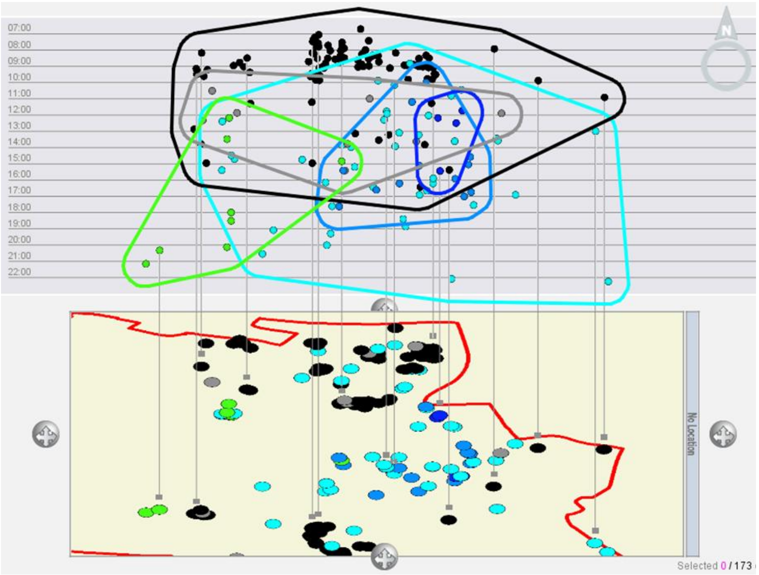

Figure 6. CTS for arrivals by purpose in most popular ward SAS (n=173)

By way of visual comparison, the compressed time status (CTS) stationary space closely matches its RTS counterpart spatial space size but changes the temporal boundary demarcation (Figures 5 and 6). This is expected as the arrival location is dependent on its time stamp. The CTS provides a more detailed account of the activities in TSAS. As expected, work and work related activities fall within the traditional mandatory normal working hours which tend to be from around 8am to 5pm. However, there are various types of flexible working arrangements in the UK which may explain the few black dots from 10am onwards as shown in Figures 5 and 6. The shift of arrival activities for *home* also makes sense as they fall in the second half (pm) of the day.

What follows is the visualisation of temporal dimensions of *departures* within the same most popular SAS but with respect to the departure activities in the ward area. The maps below use the same coloring scheme as before for the arrival activity analysis. Figure 7 shows temporal spaces of departure activities in the most popular SAS and in the real time status. Most of the activities are home departure activities and spread over October and November. Temporal space for food shopping activity is spread wider than non-food shopping. The compressed time status stationary space closely matches its RTS counterpart with a change in the temporal boundary demarcation (Figures 7 and 8).

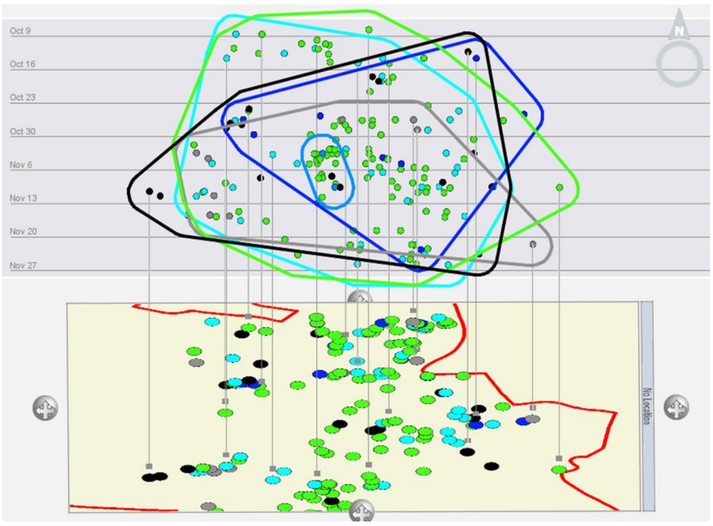

Figure 7. RTS for departures by purpose in most popular ward SAS (n=172)

Figure 8 shows the CTS for departures by purpose of activity in the most popular ward SAS area. Departure activities, with the aim of going home, cluster around 5.30pm which seem to be roughly around most official work closing hours. All other activities do not seem to follow any hourly pattern during the day. Spatio-temporal activity spaces for non-food shopping activities were relatively constrained to a small area.

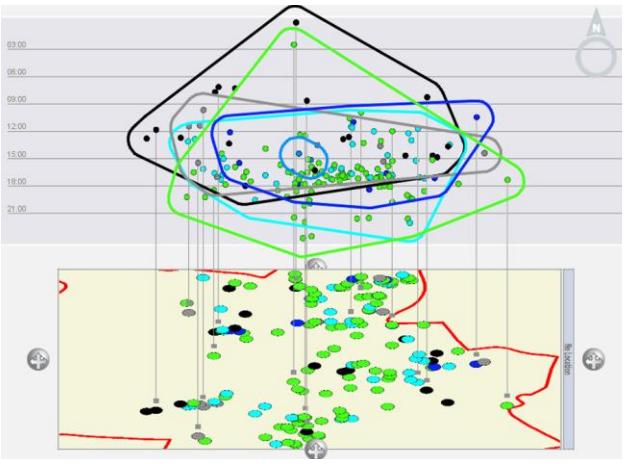

Figure 8. CTS for departures by purpose in most popular ward SAS (n=172)

3.2 Advanced analysis

In order to identify standard trends within the already identified most popular wards and output areas, standard deviational ellipses for stationary activities (i.e. departures and arrivals activities) were generated and overlaid on cycle infrastructure data such as cycle parking locations provided by Newcastle City Council. Figure 9 shows these ellipses denoting directional trend of stationary activities for areas within the most popular SAS areas. The orientation of confidence ellipses indicates the actual size of the (stationary) activity space, while their use is to explain trends in spatial behaviour and permits analysis beyond the purely descriptive level. Figure 9 (left) shows trends of *departure* stationary activity spaces by purpose and with locations of cycle parking facilities for public use that are managed by the Newcastle City Council. The figure shows the trend of activities for both popular ward and OA areas. Activities shown in the figure are those having at least six departure activity locations and the outside grey boundary is Westgate electoral ward. The work departure stationary activity spaces hold about seven of the cycle parking facilities. Food shopping departure activity spaces for both ward and OA areas appear to follow the same directional distribution. There is evidence in the figure that the activity spaces (i.e. the computed ellipses) have some cycle parking facilities, but assessing whether these provisions are enough for the respective activity spaces demands requires additional fieldwork. Figure 9 (right) shows *arrival* activity spaces for the same ward and OA areas together with the spatial locations of cycle parking facilities. The OA boundary is in light red while that of the ward is the larger grey boundary. Arrival activities for the purposes of food shopping are virtually non-existent in the popular areas. Arrival activities for the purposes of work appear visible in both the most popular ward and OA areas. These findings can be useful in considering daily accessibility issues within this area, such as access to secure parking locations.

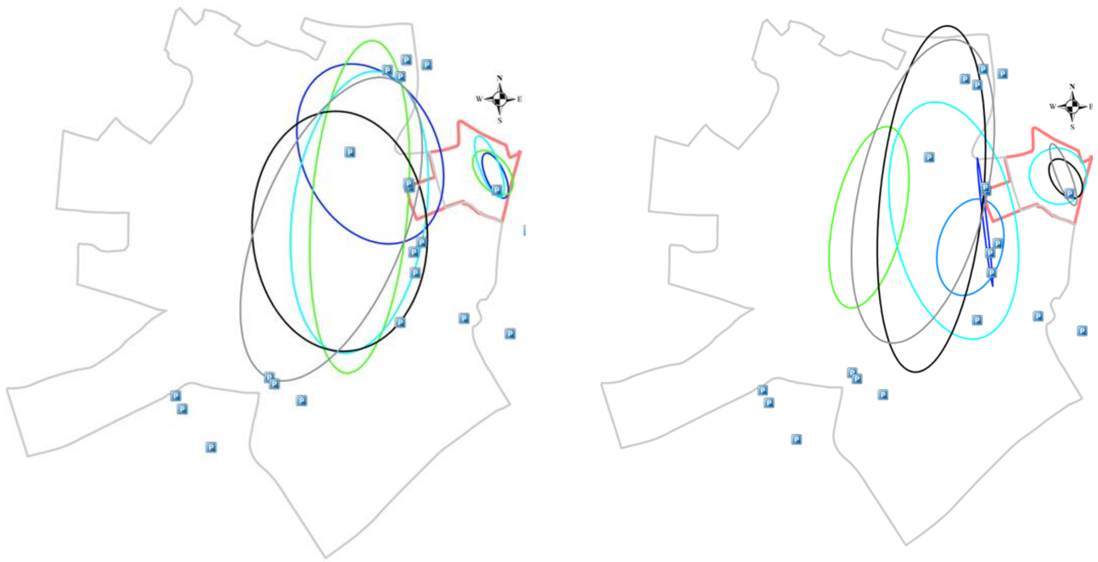

Figure 9. Trend (Standard Deviational Ellipse) for *departure* activities (left) and for *arrival* activities (right) for electoral ward and OAs

Based on the two selected geographies, Wards and OAs, it is possible to determine areas exhibiting motility by using the actual cycling flows as input. We define a geographical space G so that it consists of areas Ai = [A1, A2, …, An-1, An] that share adjacent boundaries. We also have motile activity across these areas A defined as Ti = [T1, T2,…, Tn-1, Tn]. A set of motile activity spaces (MAS) can be represented as AT= [AT1, AT2, …, ATn-1, ATn] on the condition that T crosses A. The AT with the highest frequency of motile activities becomes the most popular MAS and therefore deserves further attention in order to visualize motile activity spaces from actual cycling flows.

The total number of motile activities within each MAS, for ward and output areas, were aggregated to identify the highest frequent activity value. The refined GPS point datasets representing the isolated cycle trips and for each identified MAS were extracted to aid in the visualisation of the temporal dimension of activities. The activities in the selected MAS areas were then visualized in Space-Time Cube using both RTS and CTS approaches and the GeoTime software from Oculus was used for the visualisation. Once the MAS with highest frequency of motile activity were detected, the pointsets were used to extract the spatio-temporal information for the visualisation. Each ward/OA polygon was given a summary of the numeric attributes of the polylines (i.e. trip segments or entire trip) that spatially intersect it and a count field that shows how many polylines intersected it. Based on the count field, the highest total count was selected and its corresponding code checked to trace the area name per the census given codes. For the most popular MAS, South Jesmond emerged first followed by Westgate with 473 and 472 total mobility traces respectively. Figure 10 shows the CTS and RTS of motile activities of the most popular ward. The findings also suggest that cyclists are active during working hours as seen from the time scale on the left hand side of the figure. The top graph of Figure 10 shows spatial and temporal structures of how hourly and monthly motile activity patterns emerge within South Jesmond ward. Morning peak time of motile work activities appears to be around 9am for daily patterns within the popular MAS. Evening peak time of same activity is around 5.30pm when most of them appear to be home activities as shown in Figure 5.

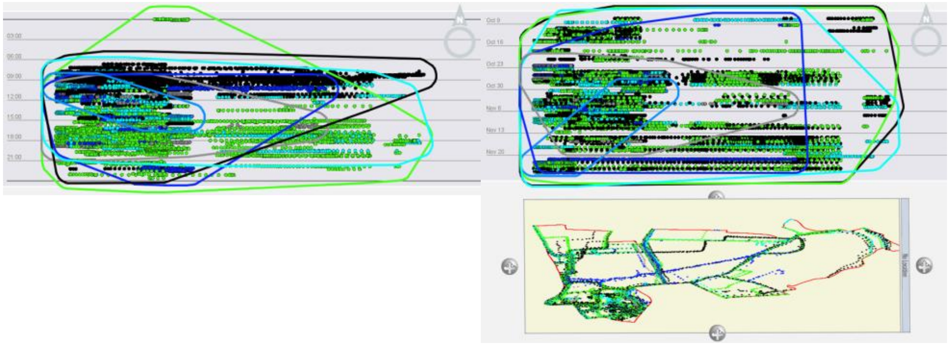

Figure 10. CTS and RTS for popular ward MAS and trip purpose

To further understand areas within South Jesmond where significant motile activities occurred, standard directional ellipses were generated based on purpose namely work, work-related, food shopping, non-food shopping, home and any other (e.g. home, visit etc.). Figure 11 shows the standard distributional trends based on activity purposes suggesting that non-food shopping activity trends within the area are different from actual food shopping activities. It is also clear in this image that non-food cycling behaviours deviate geographically from all other cycling behaviours within the most popular ward MAS area.

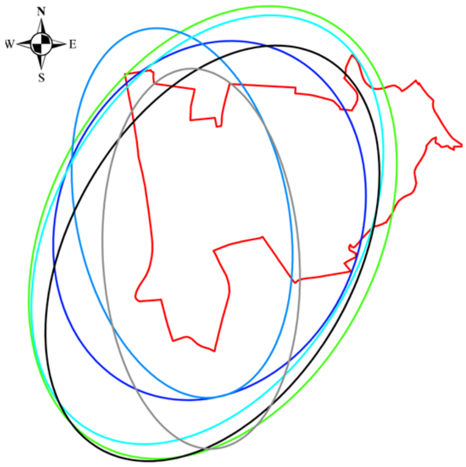

Figure 11. Standard directional distributions of popular MAS ward

The most popular OA was also in South Jesmond with a total count of 334 motile activities. Figure 12 shows the two dimensional views of most popular OA MAS area using both RTS and CTS respectively. Similar to the ward area pattern, cycling to work daily peak times were found to be around 9am while a similar pattern followed later around 5.30pm. It is suggested here that most of the peak cycling activities around 5.30pm represented return journeys back home with a few for other purposes. In order to understand the "utilitarian" activities within the identified MAS areas, the computation of standard directional distribution by generating ellipses based on trip purpose namely work, work-related, food shopping, non-food shopping and any other (e.g. home, visit etc.) were generated to show varying spatio-temporal structures of these activities. The findings suggest that non-food shopping activities within the area deviate from all other trends with different purposes at the OA level (Figure 13). Similar characteristics of purposed-based activity trends occurred at the ward level in Figure 11.

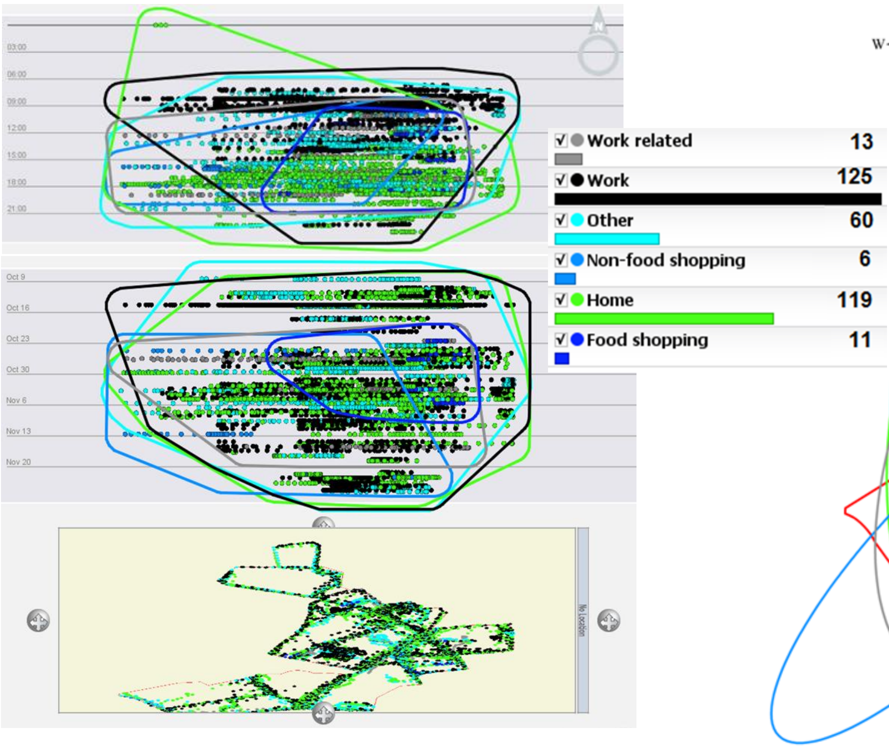

Figure 12. CTS and RTS for popular OA MAS and trip purpose (n= 334)

Figure 13: Standard directional distributions of popular OA MAS

4. Discussion and Conclusion

In this paper, we demonstrated how cycling behaviours can be analysed and visualised in a meaningful way. First, the paper contributes towards the visualisation of spatio-temporal aspects of cycling behaviours, thus adding to an existing body of knowledge on the use of visual analytical techniques for understanding travel behaviour (Van der Spek, 2009; Schonfelder and Axhausen, 2010). In addition, insights into travel behaviours of urban cyclists within the British context and around the study area are explored, adding to our understanding of actual travel behaviours of urban cyclists. Both stationary and motility are considered here as activities and their activity spaces were identified for Wards and Output Areas (OAs) as defined by the 2011 census geography. These two geographical levels are used for two reasons. OAs are the smallest areas that census data is provided for while preserving confidentiality, so they can be useful when comparing values from the census. Wards, as basic administrative blocks where councillors are elected can help create awareness among policy makers about what to do in order to improve cycling uptake. Following on from Broach et al's (2012) study in Portland Oregon, this study highlights the differences in route and destination choice decision making between commuting and other utilitarian trips among utility cyclists in the North East of England. The novel use of SAS and MAS as a means of profiling activity spaces adds to the current body of knowledge on activity-based analysis as well as on space-time geography. In a broader sense, the available concepts in the visual analytics framework have also been expanded.

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Biography

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