Visualizing Bicycle Hire Model Distributions

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Fig. 1. Location of bicycle hire docking stations in central London. Each station is represented by a rectangle sized by the number of bicycles that may be docked and coloured by their full/normal/empty status.

Index Terms—visualization, bicycle, OD map, origin destination, treemap, simulation.

1 INTRODUCTION

In July 2010, Transport for London launched the *Barclays Cycle Hire Scheme* [4] allowing members of the public to hire a bicycle from any of around 350 docking stations located in central London. Users are encouraged to take short journeys between docking stations by making hire of a bicycle free (after membership fees) if returned to any docking station within 30 minutes. Docking stations are located such than each is never more than 300m from another station (see Figure 1). A total of about 5000 bicycles are used by the scheme at any moment in time with approximately 8100 docking station places available. The scheme is currently only available to registered users who sign up via the web, although it is planned to open the scheme to casual users on a pay-per-use basis in early 2011. It is anticipated that when fully implemented, 400 docking stations and 6000 bicycles will be available.

In common with similar schemes in other cities (e.g. Dublin, Paris, Melbourne), the challenge for implementers of the scheme is to ensure that there are both sufficient bicycles and sufficient spaces for docking available at each station. This can be achieved by supplementing the natural flow of bicycles by users with additional tranportation of bikes from full stations to empty ones. This can be regarded as an example of *fleet management* [1]. This paper considers how geovisualization

can be used to support fleet management through monitoring the geographic distribution of bikes in the scheme and the integration with simulation modelling of bike journeys.

A number of web sites and services exist to support users of the scheme in locating docking stations and assessing bicycle availability. Those that represent the geography of stations tend to map docking stations using point-based symbolisation at their geographic location (e.g. [3], [2]). While this allows precise location to be identified, it leaves little graphical space for supplementary information without adding extra interaction. We use an alternative approach of mapping docking stations as a one-level *spatial treemap* [7] (see Figure 2) in which each node is sized equally and contains graphical symbolisation that reflects station status and history. This information is updated in real-time as users dock and remove bicycles from each station.

2 DOCKING STATION CHARACTERISATION

The primary purpose of the geovisualization here is to characterise and predict the usability, and hence the need for intervention, for each station. Prediction relies on both a spatial and temporal characterization of trends in station usage. Temporal trends can be assessed by showing number of docked bicycles over a previous period (e.g. last 24 hours) as a timeline in each station. By maintaining their approximate geographic distribution, spatial trends such as movements from core to periphery over time can be identified (see Figure 3).

Temporal trends can be identified by examining the time lines directly, or by statistical comparison with trends over similar weekday or weekend periods. Thus stations that are filling or emptying more

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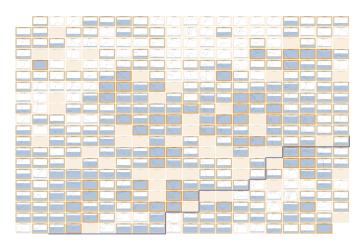


Fig. 2. Spatial treemap of docking stations showing number of docked bicycles (height of blue rectangles) and three-level status (dark brown border: full; mid-brown border: normal; light brown border: empty. Solid pale brown rectangles represent planned but non-operational docking stations. The river Thames is shown as a dark blue line for added spatial context (compare with Figure 1).

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Fig. 3. Zoomed view of docking stations showing modelled movement that results in movement from the core (bottom left) to the periphery (top right). Each graph shows number of docked bikes (vertical axis) over time (horizontal axis).

quickly than expected can by symbolised. This is particularly useful when exploring the effect of external events such as weather changes or problems with public transport on cyclists' behaviours.

Docking station usability is affected by the probability of a station having no spaces available in which to dock a hired bicycle or the chances of there being no bicycle available to hire from the station. While a station need only have one space or one bicycle to make it usable for an individual, low numbers of bicycles or spaces increase the chances of the station becoming unusable before it can be restocked or managed. We therefore model usability be measuring small numbers of bicycles/spaces below a cut-off value K, which we set to 4 bicycles/spaces in our modelling. Weighting decreases exponentially towards 0 as shown in Equation 1.

$$usability = \sum_{i=1}^{n} \frac{1 - \frac{\lfloor \frac{2K}{2b} \rfloor + \lfloor \frac{2K}{2c-b} \rfloor}{2K}}{n}$$
(1)

where b is the number of bicycles at a docking station of capacity c and n is the number of times station status is measured. This gives a scaled value between 0 (never usable) and 1 (always usable) which we can symbolise to investigate the need for fleet intervention and its spatial structure.

3 MODELLING BICYCLE JOURNEYS

To gain further insight into predicting usage trends we model bicycle journeys between stations and assess their effect on docking station levels. Using a random walk model and a probabilistic model of bicycle docking and removal, we can simulate hire and journey behaviour. By weighting journey direction as a function of location, we can simulate the tidal commuting flow that dominates observed patterns of usage. We visualize journeys using the origin-destination map or *OD Map* [8]. This is simply a reordering of the cells of an OD matrix [5] [6] into a two-level treemap. Thus each large cell in the treemap representing a docking station shows all the destination docking stations of journeys that started in that originating station. (see Figure 4). This provides a scalable means to visualize many origin-destionation patterns over time and compare modelled output with observed journeys.

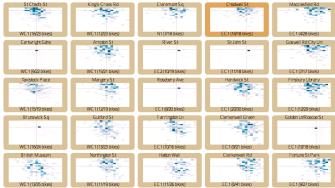


Fig. 4. Zoomed view of OD map showing destinations of bikes (blue rectangles) that were removed from selected destinations (large rectangles). Using a random walk model of bike movement there is considerable variation in origin-desintation patterns. For example St John St and Rosebury shows very local movement to Harwick St, while Hardwick St shows destinations over a much wider region.

4 CONCLUSION

Initial results of the random-walk models visualized as OD maps suggest that the precise geographic placement of stations can produce significant heterogeneity in journey patterns. This provides a useful tool to assess the effect of introducing new stations into the scheme. Visualisation of station fullness, and hence usability, over time shows where the greatest pressure points are at which times of day. This provides a useful tool for fleet management and the redistribution of bicycles across London. We are currently working on developing both the modelling and visualization tools to allow operational management of bicycle transport vehicles in real-time.

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