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Movement Pattern Analysis in ‘Smart Cities’

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1. Introduction

To design and manage cities for people it is essential to know how streets and public spaces are being used and how people move around. The classic approach to collect such data is to make sample counts of people at points of interest and conduct qualitative urban analysis (Bauer et al. 2009, Gehl and Svarre 2013), but in ‘Smart Cities’[1] movement or ‘mobility’ data from a wide range of sensors will be available online for real time analysis (Batty et al. 2012, Tao 2013; Townsend 2013). This calls for the application of analytical methods from the field of Movement Pattern Analysis.

In this short paper I will discuss some ideas and challenges on data capture and analysis of movement data for pedestrians in a ‘Smart Cities’ perspective that I have encountered in my ongoing PhD project with the working title ‘Understanding Human Movement Patterns in Urban Spaces.’

2. Motivation and research questions

The introduction of smartphones in the past few years has enabled people to locate, track and share their position to within a few meters in real time. This has at the same time opened up for new ways to collect data on people’s movements by taking advantage of the phone’s signals and sensors such as Bluetooth, Wi-Fi and Global Navigation Satellite System (GNSS) (Delafontaine et al. 2012, van Schaick and van der Spek 2008, Shoval and Isaacson 2007, Shoval 2008, Zandbergen 2009).

Even though smartphones have revolutionized the ways to collect movement data there are still limitations in the spatial and temporal accuracy of the data. In urban canyons GNSS based location fixes can only be trusted to be within ± 5-10 m of the real position once per second. With Bluetooth and Wi-Fi tracking networks it is only possible to track the signal strength of a given device, the duration it has been in range of a scanner, and the sequence of which it was detected by different scanners in a network. Furthermore smartphone based data can only be sampled for people carrying such devices.

Smartphone based data collection is thus excellent for studying movement on the city wide networks, i.e. patters on the *macro* scale, but they are not accurate enough for research on detailed movement patterns on the *micro* scale for instance when studying movement patterns in an urban plaza. This instead requires accurate and simultaneous tracking several of individuals who may move close together and where the movement of each individual depends upon interactions with others as well as on the physical layout of the place and attractors in the space traversed (Moussaïd et al. 2010, Timmermans 2009).

[1] To borrow a term from the world of hard disk technology, the ‘*SMART*’ in ‘Smart Cities’ can be thought of as a ‘*Self-Monitoring, Analysis and Reporting Technologies.*’

Video based Computer Vision (CV) tracking is a more feasible way to collect data on this scale, but it is also not perfect despite rapid improvement of this technology in recent years (Moeslund et al. 2011). For recordings with oblique angels people can occlude each other as they pass in front of a camera, and some individuals move too close together for CV algorithms to distinguish them. Also the further away objects are in a camera’s Field of View (FOV) the smaller they appear which makes it harder for CV algorithms to detect and distinguish individuals. Furthermore a camera FOV can only cover a limited study area. Multiple cameras with overlapping FOVs can be used, but still several cameras will be needed to cover larger plazas. This said a CV system is still superior to smartphone based data collection on the *micro* scale since it is able to capture relative movement behaviours and interactions between individuals (Laube, Imfeld, and Weibel 2005, Laube, van Kreveld, and Imfeld 2005), as well as to give an idea of the context the behaviours happen in. A thorough review of the pros and cons of the different technologies for pedestrian behaviour monitoring can be found in Millonig et al. (2009).

Motivated by these considerations my PhD project is on developing ways to capture people’s trajectories in urban spaces both on the *macro* and *micro* scales, and make movement data queryable in space and time and able to be analysed in relation to behaviours. The research questions I currently work with are:

How can data on human movement in urban spaces on different scales be captured, stored and analysed to reveal spatio-temporal patterns and spatial behaviour?

How can the quality of tracks obtained from Computer Visions tracking algorithms be assessed in terms of accuracy and completeness?

How can tracks of individuals recorded with GNSS devices be related to their respective high detailed tracks from a CV tracking system in Areas of Interest where both types of tracks are recorded?

3. Data and methods

To take on the challenge of the *micro* scale tracking I have worked on a method using thermal cameras and Computer Vision technology in collaboration with the Visual Analysis of People Lab at Aalborg University (Gade, Jørgensen, and Moeslund 2012, Poulsen et al. 2012). Thermal cameras have the advantage over normal RGB cameras that they can operate independent of light, and that privacy issues can be neglected as the cameras literally take the temperature of city life with no risk of revealing individuals identity from the video stream. By using a homography matrix to transfer between image and real world coordinates (Criminisi 1997) the method enables recording of georeferenced positions of individuals in a scene 30 times per second with a spatial accuracy about 25-100 cm depending on peoples’ positions in the FOV. The method thus enables extraction of individual’s tracks for analysis of people’s movements in relation to others and to features in the place.

Figure 1. The two scenes recorded by the thermal camera in our pilot study. Tracks captured by manual digitizing in T-Analyst are overlaid on the image to the right.

In June 2013 we conducted a pilot study at the Kultorvet plaza in Copenhagen. A single thermal camera was used (see video of the concept at http://bit.ly/1qbUlFK). To assess the quality of the CV trajectories in terms of their completeness and accuracy a representative sample of the CV tracks need to be evaluated against Ground Truth (GT) trajectories. For this I have manually digitized the GT trajectories of all individuals in one minute of video from the left view and five minutes from the right view displayed in figure 1. This has been done in T-Analyst developed at Lund University (http://www.tft.lth.se/video/co_operation/software/. See also video of the concept at http://bit.ly/1lrKzMP). The spatial accuracy of the tracks obtained from the videos is visualized in figure 2.

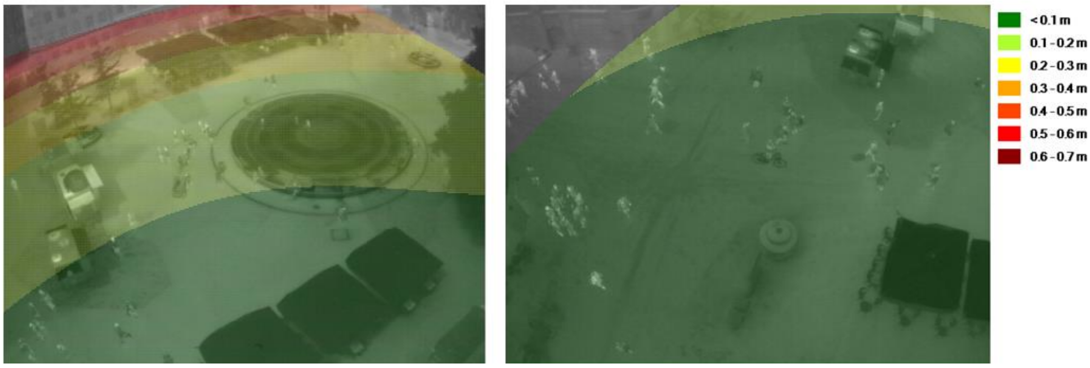

Figure 2. The spatial accuracy of the video tracking visualized for the two views. The images are generated in the T-Analyst software.

At the moment work is ongoing to develop methods in the GIS domain to compare the CV and GT trajectories in terms of computing the percentage of the trajectories that are either equal, nested, overlapping, touching internally or externally or disjoint (Egenhofer 1994), and which snapping tolerance that is acceptable between two CV and GTs track representing the movement of the same individual.

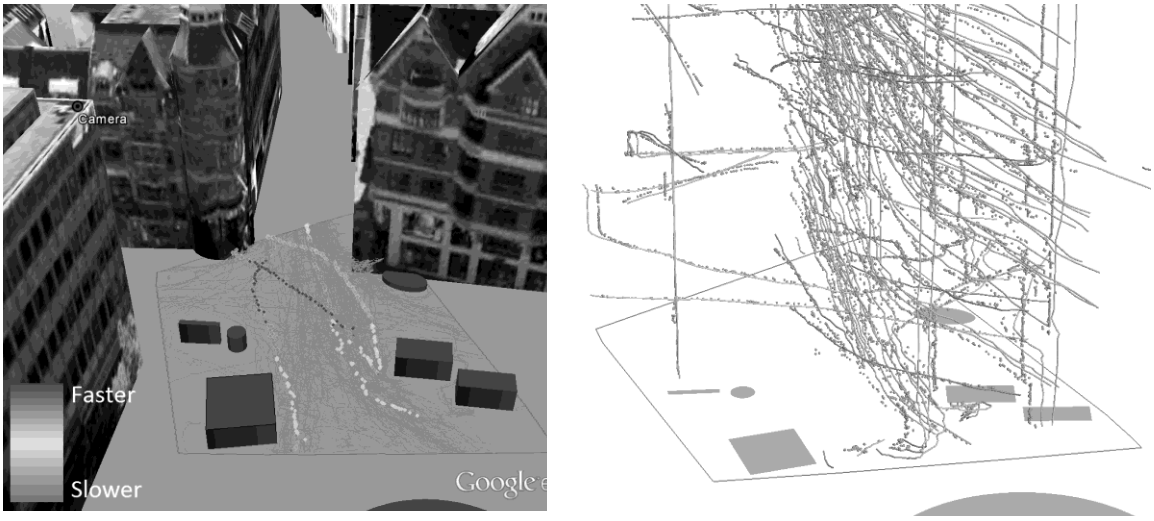

Figure 3. The left image displays one of the tracked scenes in Google Earth showing all the CV tracks captured over a five minutes period. Four individual simultaneous tracks are highlighted and shaded according to speed as an example of a movement parameter derived from the tracks. On the right image tracks from the same scene are visualized in a time-space cube. The dotted tracks depict the CV tracks and the solid tracks the manually digitized GT tracks. The task is to assess the quality of the CV tracks in relation to the GT tracks.

To visualize the data I have constructed space-time cubes (STC) depicting the CV and GT trajectories (see example in figure 3). While going through the videos to digitize the GT tracks I have identified characteristic movement behaviours of the individuals in the scene such as meeting, flocking, avoidance, and following a leader (Gudmundsson, Laube, and Wolle 2012). I have also found interesting movement patterns such as “facers” working for a charity organisation attempting to stop people in the street to recruit them. An example of this is displayed in the STC in figure 4.

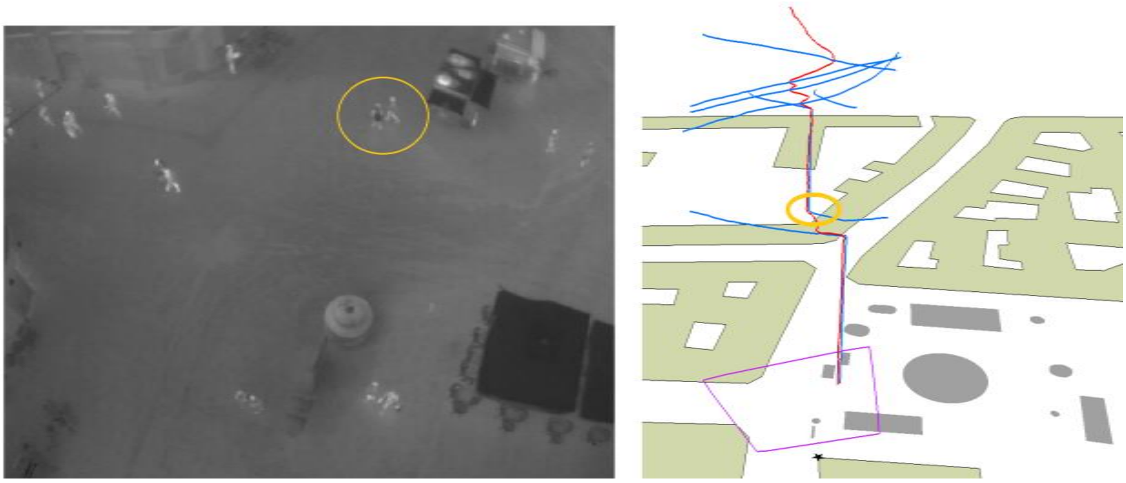

Figure 4. The right image depict the GT tracks of a “facer” (red) and the people approached (blue) in an STC. The long vertical lines show periods where the facer is successful and gets to talk to someone (seen in the first parts of the track from the bottom). In the end of the sequence the “facer” is unsuccessful as people walks by him without stopping (seen in the top of the track). The marked area in the thermal image to the left relates to the marked sequence in the STC.

4. Further research and perspectives

Based on the data and experiences gained from the pilot study we are preparing a full scale experiment using multiple thermal cameras with overlapping FOVs to be carried out over a sustained period of time. In this process it is being considered if a stereo camera setup will add additional value to the data, even though this technique will not solve the problems with people occluding each other in front of the cameras in non-nadir views. To deal with these issues the scene needs to be recorded from several angles to ensure sufficient coverage. In order to optimize the placement of cameras 3D viewshed analyses of the scene in GIS will be undertaken.

During the study we plan to track a sample of volunteers by using tracking apps on their GPS enabled smart phones in order get simultaneous tracking data from both video and GPS. In the area tracked with thermal cameras we will have some of the volunteers perform predefined standard movement patterns and behaviours to obtain data for these with both tracking technologies. To ensure that the GPS tracked people can be identified in the thermal images it is being considered to mark them with InfraRed Light Emitting Diodes (IR-LED).

A central part of the study will be to set up a Moving Object Database to store, query, and analyse tracks obtained from different tracking technologies and try to relate them based on methods of trajectory similarity analysis (Dodge 2011, Pelekis et al. 2007, Ranacher and Tzavella 2014). For this we plan to use PostGIS and the HERMES MOD extension (Pelekis and Theodoridis 2014). Due to the difference in spatial and temporal resolution between video and GPS the two tracks of the same individuals might be difficult to relate perfectly. Still, if they can be related to some extent, the method can serve as a "magnifying glass" to reveal *micro* movement patterns in predefined Areas of Interest when conducting *macro* scale tracking studies. The long term goal with this research is to be able to extract movement parameters from the different types of tracks across scales, which can eventually be used for calibration of pedestrian models (Castle and Crooks 2006).

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