Studying spatial effects on human mobility patterns using agent-based simulations

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1. Random and goal oriented walk models

To simulate human movement in a street network, we setup some random walkers which can hop from one street to another arbitrarily. The hopping behaviour is defined at a topological level in which individual streets are represented as nodes and street intersections as links of a connectivity graph (Figure 1). On the other hand, the simulation has yet to be based on a geometric level in order to mimic a sort of network constrained movement. That is, within an individual street, the random walkers persistently move along the street until they reach the next street that intersects with the current one. As soon as the random walkers reach the intersection, a decision as to which next street has to make, and then move towards the next intersection, so on and so forth. The random behaviour is obviously occurred at the topological level rather than at the geometric level.

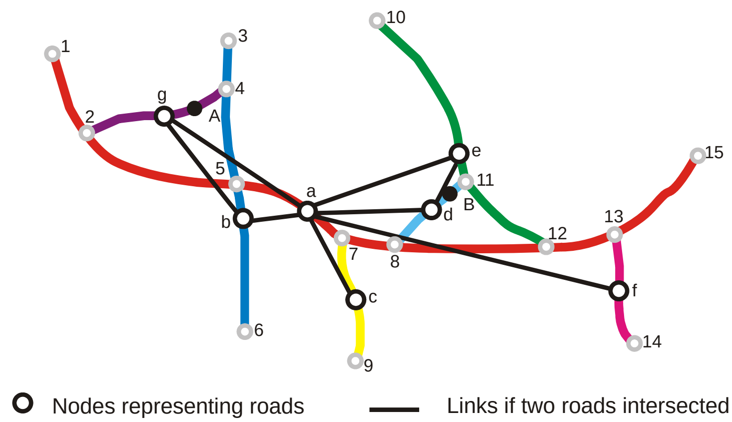

Figure 1: A connectivity graph based on street-street interaction

The random walker model can be easily adjusted to be a realistic and goal oriented human mobility model. Given that a person wants to go from location A to B (Figure 1), located respectively in street g and street d, he or she would walk (1) along street g and towards intersection 2, (2) along street a, and towards intersection 8, and (3) along the street d, and towards the location B. To this point, we have two mobility models: one random and another goal oriented. We will illustrate a fact that traffic flow in terms of how much flow in individual streets is the same for both random walkers and goal oriented walkers. It is the underlying space (street network or street length, O/D distribution and walk length) that determines the traffic flow distribution among individual streets, and mobility behaviour (random or goal oriented) has little effect on the flow distribution.

2. Simulation settings

It is illustrated that street lengths are power law distributed (Jiang 2007). We have observed (Jiang et al. 2009) that the origins and destinations (O/D) are not evenly, but rather diversely distributed. It implies that over 80% O/D are within a few hotspots such as the central station, hospital, and city centre; and other 20% O/D are scattered elsewhere. We have also found (Jiang et al. 2009) that trail lengths are power law distributed, indicating that a majority of people travel fair short distances, but a minority of people travel very long distances. To this point, we have three parameters that are power law distributed: (1) street lengths, (2) O/D distribution, and (3) walk lengths. In the previous study (Jiang et al. 2009), we adopted random walkers to move around in a street network, given the three parameters are power law distributed, and found that simulated random walkers flow agree very well with the observed traffic flow. This result indicates that random or goal oriented mobility behaviour has little effect on mobility patterns.

To further verify this finding, we adopted both the random and the goal oriented walkers to simulate and compare the simulated flow with the observed traffic flow. The simulations were done in a large street network with over 4000 streets generated from over 10 000 street segments (Jiang et al. 2009). In this study, we examined how the second and the third parameters (i.e., whether or not they are power law distributed) have effects on human mobility patterns, given the first parameter (street length) is power law distributed. Figure 2 depicts four scenarios, in which both random walker flow and goal oriented walker flow are compared with the observed traffic flow. We set up 500 walkers for each type to move at a persistent speed of 18 km/h for seconds. After the simulations get saturated, we put them in comparison with the observed traffic flow. The correlation co-efficient R square values are shown in the next section.

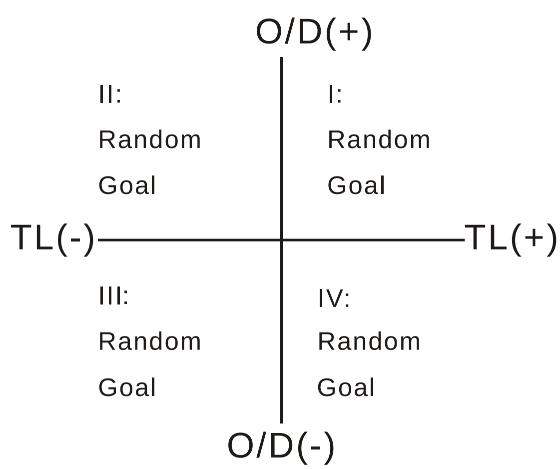

Figure 2: Different simulation scenarios given that the street lengths are power law distributed
(NOTE: Origins and destinations (O/D) are power law distributed in space (+) or not (-); trail lengths are power law distributed (+) or not (-))

3. Results

Figure 3 presents the correlation co-efficient R square values between the simulated flow and the observed flow. It indicates that O/D distribution and trail lengths have an important effect on the overall flow distribution. When the power distributions of O/D, and trail lengths are violated (II, III, and IV), the correlations are not good enough.

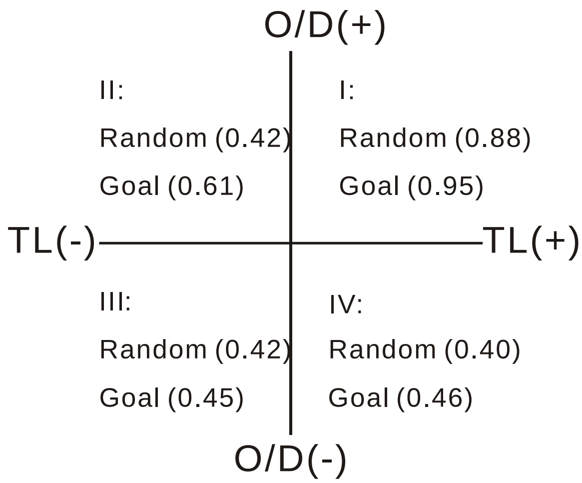

Figure 3: R square values indicating correlations of flow between the simulated and the observed

4. Related work

In the past years, there has been considerable interest in modeling and observing human mobility patterns by tracking dollar notes (Brockmann, Hufnage and Geisel, 2006), mobile phones (Gonzalez, Hidalgo and Barabási 2008), and GPS units (Rhee et al. 2008). All these studies are based on the assumption that the underlying space is a Euclidean space, where people can move from anywhere to anywhere else. These studies set a clear difference from the study by Jiang et al. (2009), where people's movement is constrained to roads only. The examination of the road constrained movement at a very fine scale leads to in-depth insight into the human mobility patterns. This study found that human movement is characterized by power law and levy flights behaviors, and concluded that human movement at a collective level is mainly determined by the underlying power law nature of space, i.e., the three parameters are power law distributed.

5. Conclusion

In this paper, we adopted both random and goal oriented walk models for simulations of mobility patterns, and examined the spatial effects under the four different scenarios. We found that as long as the three parameters are power law distributed, random or goal oriented mobility behavior has little effect on the overall flow distribution. In other words, we can predict traffic flow at a collective level. This collective traffic flow in essence is different from the individual flow or trajectories which are too complex to predict.

References

Brockmann D., Hufnage L., and Geisel T. (2006), The scaling laws of human travel, *Nature*, 439, 462 – 465.

Gonzalez M., Hidalgo C. A., and Barabási A.-L. (2008), Understanding individual human mobility patterns, *Nature*, 453, 779 – 782.

Jiang B., Zhao S., and Yin J. (2008), Self-organized natural roads for predicting traffic flow: a sensitivity study, *Journal of Statistical Mechanics: Theory and Experiment*, July, P07008, Preprint, arxiv.org/abs/0804.1630

Jiang B., Yin J., and Zhao S. (2009, under review), Characterizing human mobility patterns in a large street network, Preprint, arXiv:0809.5001, available at http://arxiv.org/abs/0809.5001

Jiang B. (1999), SimPed: simulating pedestrian flows in a virtual urban environment, *Journal of Geographic Information and Decision Analysis*, 3(1), 21 - 30.

Rhee I., Shin M., Hong S., Lee K., and Chong S. (2008), On the Lévy-walk nature of human mobility: do humans walk like monkey? *INFOCOM*, Phoenix, AZ, US.