Network and Psychological Effects in Urban Movement

Bill Hillier and Shinichi Iida

Bartlett School of Graduate Studies,
University College London,
1-19 Torrington Place, Gower Street, London WC1E 6BT, UK
{b.hillier, s.iida}@ucl.ac.uk
http://www.bartlett.ucl.ac.uk/

Abstract. Correlations are regularly found in space syntax studies between graph-based configurational measures of street networks, represented as lines, and observed movement patterns. This suggests that topological and geometric complexity are critically involved in how people navigate urban grids. This has caused difficulties with orthodox urban modelling, since it has always been assumed that insofar as spatial factors play a role in navigation, it will be on the basis of metric distance. In spite of much experimental evidence from cognitive science that geometric and topological factors are involved in navigation, and that metric distance is unlikely to be the best criterion for navigational choices, the matter has not been convincingly resolved since no method has existed for extracting cognitive information from aggregate flows. Within the space syntax literature it has also remained unclear how far the correlations that are found with syntactic variables at the level of aggregate flows are due to cognitive factors operating at the level of individual movers, or they are simply mathematically probable *network effects*, that is emergent statistical effects from the structure of line networks, independent of the psychology of navigational choices. Here we suggest how both problems can be resolved, by showing three things: first, how cognitive inferences can be made from aggregate urban flow data and distinguished from network effects; second by showing that urban movement, both vehicular and pedestrian, are shaped far more by the geometrical and topological properties of the grid than by its metric properties; and third by demonstrating that the influence of these factors on movement is a cognitive, not network, effect.

1 Introduction

A fundamental proposition in space syntax (Hillier and Hanson 1984[1]) is that, with the kinds of exceptions noted in Hillier et al. (1987)[2], Hillier et al. (1993) [3], Chang and Penn (1998)[4] and Penn et al. (1998)[5], the configuration of the urban street network is in itself a major determinant of movement flows: that is, the number of people observed moving along the street segments, without regard to the origins or destinations, or to the reasons for choosing to move

A.G. Cohn and D.M. Mark (Eds.): COSIT 2005, LNCS 3693, pp. 475–490, 2005.

along that segment.[1] The research which supports this proposition is based on representing the street system as a network of the fewest lines that cover the system, translating the network into a graph in which lines are nodes and intersections are links (similar to what is known as 'line graph' as in Harary (1969)[8], reversing the more common 'primary' representation), and measuring configuration through topological distances in the graph, without metric weighting. The fact that strong correlations are commonly found between observed flow and such configurational measures (as in Hillier et al. 1993[3], Penn et al. 1998[5]) suggests that geometric (from the use of lines) and topological (from the use of metric free graph measures) factors are critically involved in how people navigate urban grids. However, because the reported results are about aggregate human behaviour, it has always been unclear how far they depended on individual spatial decisions, and how far they are simply mathematically probable *network effects*, that is emergent statistical effects from the structure of line networks, relatively independent of the psychology of navigational choices.

The apparent involvement of grid complexity in navigation has also brought space syntax into conflict with orthodox urban modelling, where it has always been assumed that insofar as spatial factors play a role in navigation, it will be on the basis of metric distance. However, in recent years, research results have accumulated in cognitive science which suggest that the metric distance assumption is unrealistic, not perhaps because we do not seek to minimise travel distance, but because our notions of distance are compromised by the visual, geometrical and topological properties of networks. For example, estimates of distance have been shown to be affected by the division of routes into discrete visual chunks (Golledge 1992[9]; Montello 1997[10]; Kim 2001[11]; Kim and Penn 2004[12]), by a tendency to correct bends to straight lines and turns to right angles (Allen 1981[13]),and even by the direction in which the estimate is made (Sadalla et al. 1980[14]; Montello 1992[15]; Golledge 1995[16]). As a consequence, much current cognitive work on spatial complexity explores how far route choices reflect the frequency (Duckham and Kulik 2003[17]) or degree (Conroy-Dalton 2001[18]; 2003[19]; Hochmair and Frank 2002[20]) of directional change, rather than metric distance. An obstacle to a more definitive resolution within the urban research community of how concepts of distance shape human movement—or even whether or not a general definition exists—is that no method exists to extract cognitive information from the aggregate flows in street networks, and distinguish this from emergent statistical effects of the network itself. In this paper, we seek to resolve these questions through a two stage argument. First we develop a theory of why network effects on movement flows

[1] For example, in the study of human cognition, a distinction is often made between *navigation* (a certain knowledge on the route to be followed is assumed) and *wayfinding* (no predetermined criteria is defined and therefore it involves search and exploration) (Golledge and Gärling 2002[6]), although two terms are also used interchangeably (Duckham et al. 2003[7]). Throughout this paper, the discussion of movement will only refer to the observed aggregate numbers.

are to be expected in spatial configurations in general, and why the syntactic measures of *closeness* and *betweenness* can be expected to capture them.

We then ask what remains for the psychology of navigation and suggest the answer can be found in the concepts of *distance* that must underlie the use of measures like closeness and betweenness. By using different concepts of distance in configurational analysis of urban networks, and correlating the results with real movement flows, we show how cognitive inferences can be made from aggregate movement data, and distinguished from network effects. By using this method in a study of movement in four areas of London, we also show that movement in cities reflects the geometrical and topological structure of the network configuration far more than metric distance.

2 Network Effects: Theoretical Motivation

Why and how, then, should we expect street networks to shape movement in cities? First, we must be clear about network effects—that is emergent statistical effects on aggregate movement from the structure of the network itself—and why they are to be expected in movement in urban systems.[2] First, we remind the reader of a simple yet motivating example (Hillier 1999[22]) that makes network effects intuitively obvious. Figure 1 shows a notional grid with a main street, a cross street, some side streets and a back street. Suppose all streets are equally

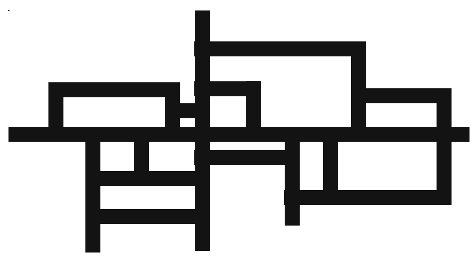


Fig. 1. Notional grid showing how the network will shape movement flows

loaded with dwellings, and that people move over time from all dwellings to all others using some notion of shortest (least distance) or simplest (fewest turns) routes. It is clear that more movement will pass through the horizontal main street than other streets, and that more will pass the central parts of the main

[2] The actual urban systems may contain many different levels of movements all of which may have a compound effect on route choice and navigation, as suggested, for example, by Timpf et al. (1992)[21]. In addition, each street segment may have a various non-physical constraints in access (for example, a restriction of entry by the direction). However, we will focus on the simplest level of movement (either pedestrian or vehicular), that is, the simple count of people or vehicles moving along a simple street system where all the streets are treated equally.

street than the more peripheral parts. This effect follows from the structure of the network, since no one needs a plan to pass through the spaces, and would hold under either assumption about distance. It is also clear that the main street considered as a whole is more *accessible* than other spaces, on either definition of distance. It will then be more advantageous to locate a shop on the main street, since it will be both easier to get to and also where people are likely to be when moving between locations. Although locating a shop is an individual decision, it is clear that the decision will be shaped first and foremost by the properties of the network. This simple example shows in a common-sense way why we should expect network effects on movement.

Now consider a more complex theoretical example. On the top left of Figure 2 is a notional arrangement of blocks with something like the degree of linear continuity between spaces that we expect in urban space. Visibility graph analysis (Turner et al. 2001[23]) shows an emergent warm colour pattern which looks a bit like a main street, with side streets and back streets, although of a rather a irregular kind. On the right we retain exactly the same blocks but move some marginally to 'just about' block lines of sight, so in effect, we change nothing but the linear relations between some of the spaces. The visibility graph analysis, shown on the same scale, shows not only a substantial loss of visual integration but also a totally transformed pattern, with little in the way of continuous structure. Spatial network seems to have lost structure as well as integration.

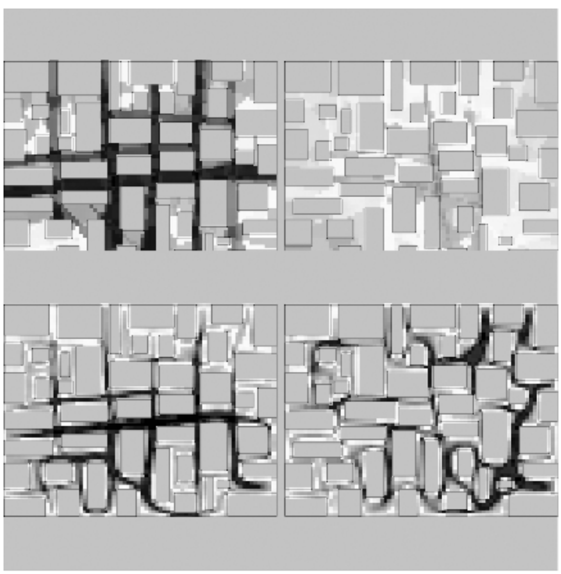


Fig. 2. Two layout showing how slight shifts in the positioning of blocks to allows or break lines of sight has major effect on degree and structure of visual integration (top row) and the traces of 10000 randomly moving sighted agents.

This is of course the well-known syntactic property of *intelligibility* (Hillier et al. 1993[3]). The r^2 between the *visual connectivity* and *visual integration* of point is 0.714 in the left case and 0.267 on the right. But this mathematical change in the network structure has consequences even for theoretical movement. In the bottom of Figure 2, we use the 'agent' facility in Turner's Depthmap software (Turner 2001[24]) to show the traces of 10000 sighted agents with 170 degrees of vision, who select a point within their field of view randomly, move towards it three pixels and repeat the process. Even with the sight and distance parameters set close to randomness (in that vision is diffuse rather than focused and distance between destination selections are short), the results are strikingly different. In the left case the highest density of traces follows the space structure to a remarkable degree, while in the right case, it spirals all over the system, reflecting the local scaling of spaces rather than overall configuration. Since the 'cognitive' structure and behaviour of agents is identical in the two cases, the differences between the trace patterns are clearly *network effects*.

3 Network Effects in Real Urban Systems

But what of real human subjects in real urban systems? Are there reasons for expecting network effects at this level? It is useful here again to distinguish between the *structure* of the graph, that is, the pattern of nodes and links, and how *distance* between nodes is to be calculated. There are (as noted in Hillier 2002[25]) in principle strong mathematical reason to expect network effects from the structure of any graph on movement, in that random one step movement in a non-bipartite graph will lead to the number of visits per node going to a limit of the degree of the node as the number of iterations goes to infinity (Norris 1997[26]; Batty and Tinkler 1979[27]). If movement is random and one step, then, the number of visits to each node will be wholly determined by the structure of the graph.

But of course human movement is neither random nor one step. For the most part it is both planned and n-step. Are there also mathematical reasons why flows arising from this kind of movement will be shaped by the network configuration? First let us consider the nature of human movement. It has two aspects: the selection of a destination from an origin; and the selection of the intervening spaces that must be passed through to go from one to the other. The former is about *to-movement*, the latter *though-movement*.

First, consider *to*-movement. From any origin, say, someone's house, we must expect that over time a range of trips will be made to various destinations, and these will be a matter of individual decision. But, over time, the choice of destinations from any origin would be expected to show some degree of statistical preference for closer rather than more remote destinations—say, by going more often to the local shop than to visit an aunt in Willesden. It does not have to be that way, but in most cases it probably will be. This is no more than an instance of what geographers have always called *distance decay*. But if there is any degree of distance decay in the choice of destinations, then it has the formal consequence that locations which are closer to *all* others in the network will be featured as destinations more often than those that are more remote—that is, more accessible locations will be theoretically more attractive as destinations than less accessible ones simply as a result of their configurational position in the complex as a whole. The bias towards more accessible locations for *to*-movement is then a network effect, due to the configurational structure of the network, even though it is driven by the accumulation of individual decisions.

This of course is to say no more than that central locations in a system are more accessible than others. But the argument becomes more interesting if we consider *variable radius* integration, that is the accessibility of nodes to its neighbouring network up to a certain graph or metric distance away. A node which is more integrated than others in its region at a given radius will also become more theoretically attractive as a destination to the degree that movement at that graph scale is preferred in the system. In other words, the network properties measured by variable radius integration can be *theoretically* expected to attract more movement to some destinations than others purely as an effect of the structure of the network, and this is of course what we find in urban reality.

But the effect of the network does not end there, since there will also be network effects on *through*-movement, more obvious than those for *to*-movement. The sequences of nodes that are available between origins and destinations will often vary with different definitions of distance (as we will see below) but whichever definition of distance we choose the available sequences are defined by the structure of the graph itself, so again we are dealing with network effects. However we define distance, in effect, the choice of routes is defined by the network.

So network effects must exist for both *to*- and *through*-movement. There will also be an interaction between them. First, every trip is made up of a pair of origin-destination, or *to*-movement nodes, and a variable number of *through*-movement nodes. But with increasing length of trip the *to*-movement pair will remain constant at two nodes while the *through*-movement node count will increase. It follows that the longer the trip, the higher will be the ratio of *through*-movement spaces to the origin-destination pairs, which of course always remain constant. We may expect then that the greater the graph length of the trip, the more it will reflect the choice, or betweenness, structure of the graph, rather than the integration, or closeness, structure.

Second, any *to*-movement bias towards integrated locations will also have an effect on *through*-movement, since routes leading to those locations will be more likely to be used than those leading to less integrated locations. It would be a simple matter to reflect this by weighting the choice measure for the integration value of destinations (see below). This combined measure should then theoretically measure both aspects of simplest path n-step movement in a system, with some adjustment for the mean length of trips. So in the 'state of nature' the graph should already have a tendency towards a certain pattern of movement reflecting the spatial configuration of the graph, and the configurational properties which produce this are exactly reflected in the syntactic measures of variable radius integration and choice, and by the relations between them.

This then is the theory of urban movement in a network considered as a graph. But how people actually move will clearly be affected by how distance is conceptualised. In what follows, we show how cognitive information on how distance concepts can be extracted from information on real flows in urban networks.

4 Varying Distance Concepts in Line Networks

The technique we propose to extract cognitive information from real flows is to take urban street networks and subject them to different mathematical interpretations according to how distance is defined, then to explore how well the different interpretations correlate with real movement patterns. The basis of the different interpretation is a disaggregated line-network model which is an extension of fewest line-network model ('axial map', originally developed by Hillier and Hanson (1984)[1]) for introducing fractional weights instead of a constant one (for example, see Turner (2001)[28], Dalton (2001[29], 2003[30]), Winter (2002)[31], Dalton et al. (2003)[32] and Asami et al. (2004)[33]). [3] We describe the construction of the model below.

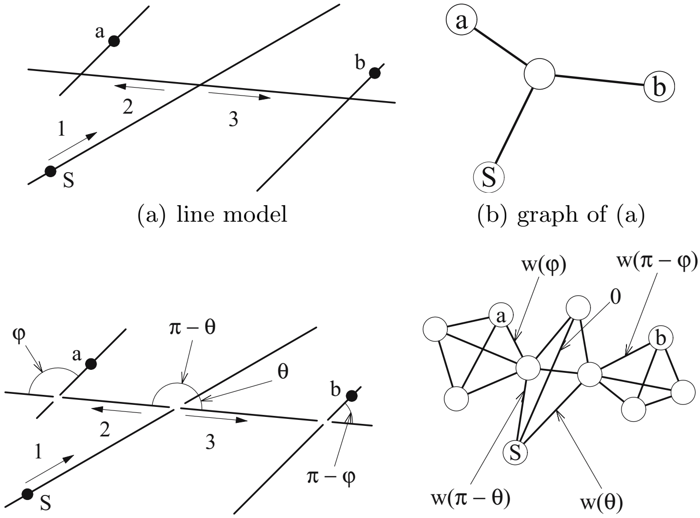
We start from the existing fewest line map and represent the street network as its graph of line segments between intersections. Figure 3(a) is an example of the unweighted line network with three lines, and its graph representation is shown in Figure 3(b).

Figure 3(c) shows how the line network is disaggregated at intersections to form a segment network, and Figure 3(d) shows its graph representation. Each line segment is represented as a node in the graph and links between nodes are intersections. The distance cost between two line segments is measured by taking a 'shortest' path from one to the other, so the cost of travel between **S** and **a** can be given as $w(\pi - \theta) + w(\phi)$, while the cost between **S** and **b** can be $w(\theta) + w(\pi - \phi)$. Three different weight definitions are then used to represent different distance cost relations between adjacent segments:

Least length (metric) The distance cost of routes is measured as the sum of segment lengths, defining length as the metric distance along the lines between the mid-points of two adjacent segments. The distance of two adjacent line segments is thus calculated as half the sum of their lengths.

Fewest turns (topological) Distance cost is measured as the number of changes of direction that have to be taken on a route. In the example shown in Figure 3(c) and (d), $w(\theta) = w(\pi - \theta) = w(\phi) = w(\pi - \phi) = 1$ (however, $w(0) = 0$).

[3] The model also has a close relevance to the street-based network models such as Jiang and Claramunt (2002)[34], Thomson (2003)[35], Porta et al. (2004)[36] or Rosvall et al. (2005)[37].



(a) line model (b) graph of (a)

(c) segment model (d) graph of (c)

Fig. 3. Line-network model and its disaggregated model with graph representation for each model

Least angle change (geometric) Distance cost is measured as the sum of angular changes that are made on a route, by assigning a weight to each intersection proportional to the angle of incidence of two line segments at the intersection. The weight is defined so that the distance gain will be 1 when the turn is a right angle. In other expression, $w(\theta) \propto \theta \quad (0 \leq \theta < \pi), \quad w(0) = 0, \quad w(\pi/2) = 1$.

These definitions reflect different conjectures in the literature as to how distance is conceptualised in human navigation. Paths between all segments and all others can then be assessed in terms of least length, fewest turns, and least angle paths. Least length paths are the shortest metric distances, fewest turns paths the least number of direction changes, and least angle paths the smallest accumulated totals of angular change on paths, between all pairs of nodes. Note that the original lines of the fewest line map will emerge as sequences of zero-change weights for fewest turns and least angle change paths. In this sense the model also allows a test on how far the focus on linearity of syntactic axial mapping is justified.

We then apply the common centrality measures of 'closeness' and 'betweenness'. Closeness, as defined by Sabidussi (1966)[38], is:

$$C_C(p_i) = \left(\sum_k d_{ik} \right)^{-1}$$

where d_{ik} is the length of a geodesic (shortest path) between node p_i and p_k. Betweenness, as defined by Freeman (1977)[39], is:

$$C_B(p_i) = \sum_j \sum_k g_{jk}(p_i)/g_{jk} \quad (j < k)$$

where $g_{jk}(p_i)$ is the number of geodesics between node p_j and p_k which contain node p_i, and g_{jk} the number of all geodesics between p_j and p_k.

This gives six different mathematical interpretations of a street system: closeness and betweenness measures applied to least length, least angle change and fewest turns weightings of relations between adjacent segments in the system. In addition, closeness measures can be assigned for every radius, defining radius in terms of the number of segments distant from each segment treated as a root. This permits experimentation with the scale at which measures operate, from the most local, to the global level.

5 Empirical Studies

We then take four areas of London (Barnsbury, Clerkenwell, South Kensington and Knightsbridge)[4] on which earlier studies (Penn et al. 1998[5]) had established dense vehicular and pedestrian movement flows at the segment level throughout the working day for a total of 356 observation 'gates'.[5] The street network for each observation area was embedded in a contextual network of 3–3.5km radius, and analysed using the segment network representation. Closeness measures were calculated for every third radius, that is up to 3, 6, 9, ... segments distant from a root segment, up to the maximum radius of the system.

Translating the numerical results of the analysis into images of the network, with segments coloured in bands of value for each measure, from black for least distance through to pale gray for most, Figure 4 shows that the different interpretations give different pictures of the 'structure' of the network, some slight, others more substantial. The upper row of figures show closeness (a: geometric, b: topological, c: metric) and the figures at the bottom betweenness (d: geometric, e: topological, f: metric). In the closeness maps (a-c), line segments in dark tone are those with the least mean distance cost from that line segment to all others,

[4] Two of the areas (South Kensington and Knightsbridge) had originally been selected to pose problems for a purely configurational analysis, in that they had large movement attractors at their heart, one a complex of national museums adjacent to a tube station, and the other a leading department store. Both could be expected to distort correlations with purely network measures, but the original study by Penn et al. (1998)[5] found consistent agreement between vehicular flows and the local closeness measure, regardless of the existence of attractors.

[5] Observation points were set up on each street segment and the number of pedestrians and vehicles that pass each observation point was counted for ten minutes in each of five time peiriods during the working day, totalling fifty minutes of observation for each point. The hourly average volume of flows were then used to see the correlation with the measures.

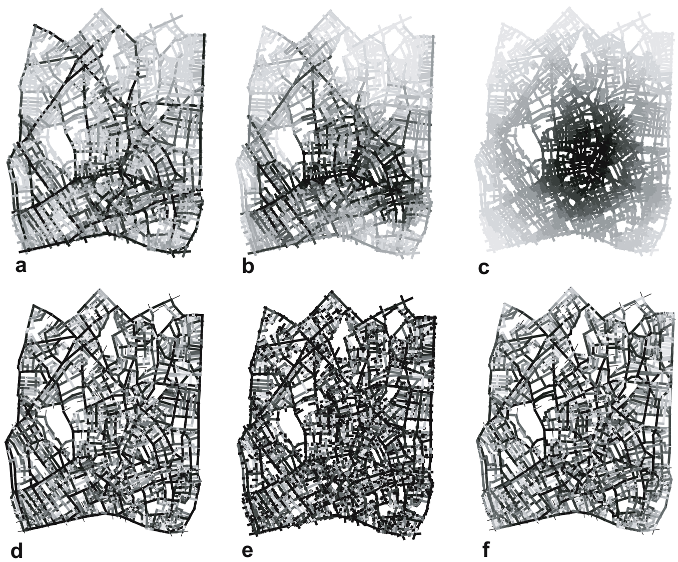


Fig. 4. Disaggregated line network models of Barnsbury area in London, each coloured up by a different measure

and shift to lighter tone as the degree of closeness declines. In the betweenness maps (d-f), line segments in dark tone are those which lie on most shortest paths between pairs of segments, declining towards lighter tone for those which lie on least. The network consists of 10897 line segments and the area covered by this model is roughly 3km in radius. The observation area was near the centre of the

Table 1. Adjusted R^2 values for correlations between vehicular flows and least sum of length, least sum of angle change and least number of turns analysis applied to closeness and betweenness measures

Area name	*Gates*	*Measure*	*Least length*	*Least angle*	*Fewest turns*
Barnsbury	116	closeness	0.131 (60)	0.678 (90)	0.698* (12)
		betweenness	0.579	0.720*	0.558
Clerkenwell	63	closeness	0.095 (93)	0.837* (90)	0.819 (69)
		betweenness	0.585	0.773*	0.695
S. Kensington	87	closeness	0.175 (93)	0.688 (24)	0.741* (27)
		betweenness	0.645	0.629	0.649*
Knightsbridge	90	closeness	0.084 (81)	0.692* (33)	0.642 (27)
		betweenness	0.475	0.651*	0.580

* Best correlation.

† Numbers in round brackets indicate best radius in segments for closeness measures.

Table 2. Adjusted R^2 values for correlations between pedestrian flows and least sum of length, least sum of angle change and least number of turns analysis applied to closeness and betweenness measures

Area name	*Gates*	*Measure*	*Least length*	*Least angle*	*Fewest turns*
Barnsbury	117	closeness	0.119 (57)	0.719* (18)	0.701 (12)
		betweenness	0.578	0.705*	0.566
Clerkenwell	63	closeness	0.061 (102)	0.637 (39)	0.624* (36)
		betweenness	0.430	0.544*	0.353
S. Kensington	87	closeness	0.152 (87)	0.523* (21)	0.502 (27)
		betweenness	0.314	0.457	0.526*
Knightsbridge	90	closeness	0.111 (81)	0.623* (63)	0.578 (63)
		betweenness	0.455	0.513	0.516*

* Best correlation.

† Numbers in round brackets indicate best radius in segments for closeness measures.

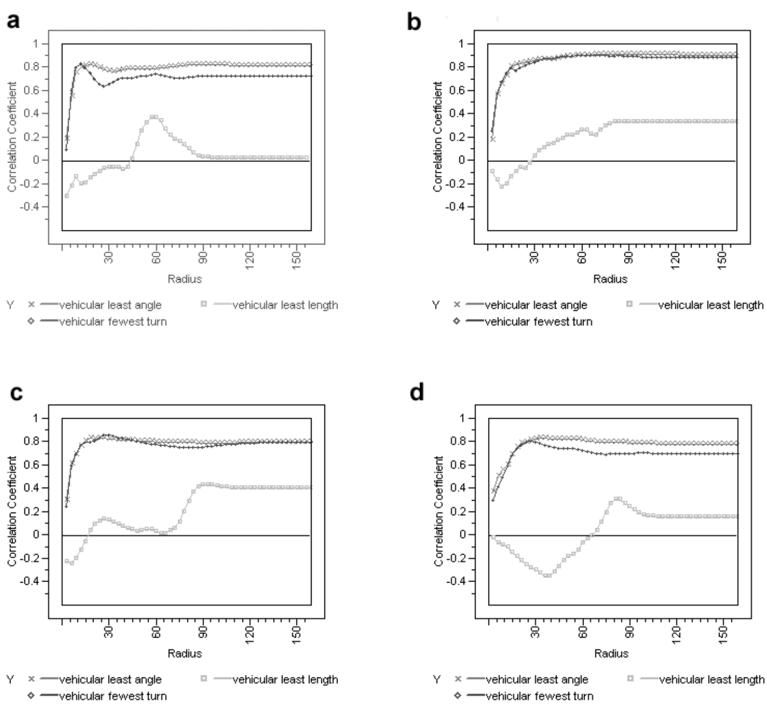


Fig. 5. Line charts showing the change in the correlation coefficient of vehicular movement with all three types of closeness measures with increasing radius

map (around 600m in radius), where vehicular and pedestrian flow data was collected. Of two measures, closeness shows a marked difference between different

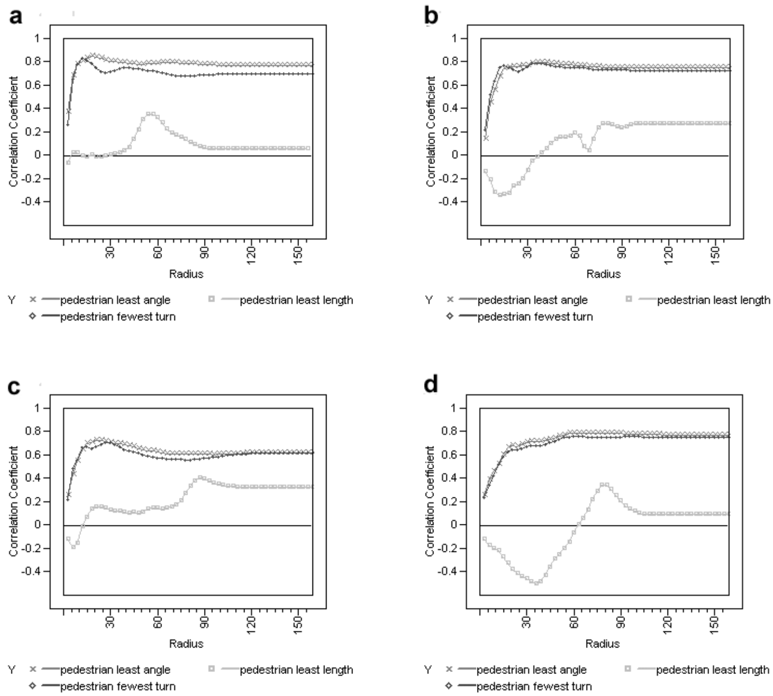


Fig. 6. Line charts showing the change in the correlation coefficient of pedestrian movement with all three types of closeness measures with increasing radius

interpretations of distance, with the metric version yielding only a concentric picture with highest closeness in the centre of the map and a smooth decline towards the edges. Betweenness shows more stability across the weights, although a more concentric picture can be observed in the metric version. Adjusted R^2 values for the correlations between closeness and betweenness measures range between 0.505–0.807 for the least angle interpretation, between 0.599–0.853 for fewest turns, and between -0.0067–0.0764 for least length. The reason for the lack of correlation for the least length version is that least length for closeness from all nodes to all others must give a result in which the closest segment to all

Table 3. Adjusted R^2 from axial radius-3 integration

Area name	*Vehicular*	*pedestrian*
Barnsbury	0.765**	0.706
Clerkenwell	0.627	0.570
South Kensington	0.819**	0.514
Knightsbridge	0.560	0.467

others is at the geometric centre, with a more or less smooth fall-off from centre to periphery, as can be seen in the concentric patterns shown in Figure 4c.

The different sets of values for segments were then correlated with observed vehicular and pedestrian flows averaged for the whole working day between 8 a.m. and 6 p.m. For vehicular movement correlations were confined to streets with unrestricted two-way flows, but for pedestrian movement the whole urban network was included (though observations made inside a college and a housing estate were not). The pattern of adjusted R^2 values for vehicular movement is shown in Table 1 and for pedestrian movement in Table 2 with a total of 48 correlations and therefore 16 possible best correlations. Correlations will be in general negative in closeness centrality (but see below) since movement should increase with less metric, angular or directional change.

The results give a consistent picture. In 11 out of 16 cases, (5 vehicular and 6 pedestrian) least angle correlations are best. In the remaining five cases fewest turns is best, but in each case only marginally better than least angle. In no case is a metrically based measure best, and in no case is a least angle measure worst. On average correlations based on least length measures are markedly lower than the other two. The pattern of correlation for the metric, least angle and fewest turns interpretations of the closeness measure with increasing radius are shown from left to right in Figure 5 and Figure 6. Each line chart corresponds to the vehicular (Figure 5) and pedestrian (Figure 6) movement data of Barnsbury (a), Clerkenwell (b), South Kensington (c) and Knightsbridge (d). Plots for least length (metric) are shown in gray, least angle change (geometric) in crossed dotted line, and fewest turns (topological) in dotted line. In all cases the correlation coefficient stabilises above a certain radius, but not necessarily at its optimal level, suggesting natural limits to the radius within which configurational measures operate. The plots show that the superiority of the least angle model is more marked than in the tabulated results in two of the four cases. We conjecture that the weakly negative correlations at low radii for metric (meaning that it is positively correlated with movement) are due to the fact that higher connectivity for a segment will both tend to produce more movement and have a higher sum of lengths, while higher sums of length at the larger scale will mean greater distance from the rest of the system and so less movement.

6 Discussion

How then are these results to be interpreted? From a cognitive point, it is clear that, unlike previous results from axial maps, the *differences* in movement correlations with the different definitions of distance cannot be network effects, since in each case the representation of the street network and its graph are identical, and all that differs is the mathematical interpretation by varying the concept of distance. The differences in correlation can then only be due to differences in the degree to which each mathematical interpretation coincides with the interpretations made by individuals moving in the system. It is then an unavoidable inference that people are reading the urban network in geometrical and topological rather then metric terms. Although it is perfectly plausible that people *try* to minimise distance, their concept of distance is, it seems, shaped more by the geometric and topological properties of the network more than by an ability to calculate metric distances. In general we might say that the structure of the graph governs network effects on movement and that how distance is defined in the graph governs cognitive choices.

These results have three implications. First, they show that it is the geometrical and topological architecture of the large scale urban grid that is, as space syntax has always argued, the most powerful shaper of urban movement patterns. These factors are not currently represented in most of the models currently in use to predict urban movement. The effect is that the design of movement systems does not take account of the primary factors which shape urban movement. Clearly, this situation cannot continue.

Second, the results show that axial graphs in their present form are in most circumstances a perfectly good approximation of the impact of spatial configuration on movement. In two of the eight cases reported,the correlation between movement and radius-3 integration is better than any of the segment analyses, and in general the spread of R^2 values for axial graph mirrors the pattern of correlation for the new, more disaggregated segment based measures.

Third, these results are the strongest demonstration to date that the architecture of the street network, in both geometrical and topological sense, can be expected, through its effect on movement flows, to influence the evolution of land use patterns and consequently the whole pattern of life in the city. This most powerful feature of the urban system can surely not continue to be sidelined in urban modelling, and the architectural effects of the large scale street network cannot be discounted.

References

1. Hillier, B., Hanson, J.: The Social Logic of Space. Cambridge University Press, Cambridge, UK (1984)
2. Hillier, B., Burdett, R., Peponis, J., Penn, A.: Creating life: or, does architecture determine anything? Architecture and Behaviour **3** (1987) 233–250
3. Hillier, B., Penn, A., Hanson, J., Grajewski, T., Xu, J.: Natural movement: or configuration and attraction in urban pedestrian movement. Environment and Planning B: Planning and Design **20** (1993) 29–66
4. Chang, D.K., Penn, A.: Integrated multilevel circulation in dense urban areas. Environment and Planning B: Planning and Design **25** (1998) 507–538
5. Penn, A., Hillier, B., Banister, D., Xu, J.: Configurational modelling of urban movement networks. Environment and Planning B: Planning and Design **25** (1998) 59–84
6. Golledge, R.G., Gärling, T.: Spatial behavior in transportation modeling and planning. In Goulias, K., ed.: Transportation Systems Planning: Methods and Applications. CRC Press (2002)
7. Duckham, M., Kulik, L., Worboys, M.F.: Imprecise navigation. Geoinformatica **7** (2003) 79–94
8. Harary, F.: Graph Theory. Addison-Wesley, Reading, Mass. (1969)

9. Golledge, R.G.: Place recognition and wayfinding: making sense of space. Geoforum **23** (1992) 199–214
10. Montello, D.R.: The perception and cognition of environmental distance. In Hirtle, S.C., Frank, A.U., eds.: Spatial Information Theory: Theoretical Basis for GIS. Number 1329 in Lecture Notes in Computer Science. Springer-Verlag, Berlin (1997) 297–311
11. Kim, Y.O.: The role of spatial configuration in spatial cognition. In: Proceeding of the Third International Space Syntax Symposium, Atlanta, GA, Georgia Institute of Technology (2001) 49.1–49.21
12. Kim, Y.O., Penn, A.: Linking the spatial syntax of cognitive maps to the spatial syntax of the environment. Environment and Behavior **36** (2004) 483–504
13. Allen, G.L.: A developmental perspective on the effects of "subdividing" macrospatial experience. Journal of Experimental Psychology: Human Learning and Memory **7** (1981) 120–132
14. Sadalla, E.K., Burroughs, W.J., Staplin, L.J.: Reference points in spatial cognition. Journal of Experimental Psychology: Human Learning and Memory **6** (1980) 516–528
15. Montello, D.R.: The geometry of environmental knowledge. In Frank, A.U., Campari, I., Formentini, U., eds.: Theories and Methods of Spatial Reasoning in Geographic Space. Number 639 in Lecture Notes in Computer Science. Springer-Verlag, Berlin (1992) 136–152
16. Golledge, R.G.: Path selection and route preference in human navigation: a progress report. In Frank, A.U., Kuhn, W., eds.: Spatial Information Theory: A Theoretical Basis for GIS. Number 988 in Lecture Notes in Computer Science. Springer-Verlag, Berlin (1995) 182–199
17. Duckham, M., Kulik, L.: 'simplest' paths: automated route selection for navigation. In Kuhn, W., Worboys, M.F., Timpf, S., eds.: Spatial Information Theory: Foundations of Geographic Information Science. Number 2825 in Lecture Notes in Computer Science. Springer-Verlag, Berlin (2003) 182–199
18. Conroy Dalton, R.: Spatial navigation in immersive virtual environments. PhD thesis, Bartlett School of Graduate Studies, University of London (2001)
19. Conroy Dalton, R.: The secret is to follow your nose: route path selection and angularity. Environment and Behavior **35** (2003) 107–131
20. Hochmair, H., Frank, A.U.: Influence of estimation errors on wayfinding-decisions in unknown street networks — analyzing the least-angle strategy. Spatial Cognition and Computation **2** (2002) 283–313
21. Timpf, S., Volta, G.S., Pollock, D.W., Frank, A.U., Egenhofer, M.J.: A conceptual model of wayfinding using multiple levels of abstraction. In Frank, A.U., Campari, I., Formentini, U., eds.: Theories and Methods of Spatial Reasoning in Geographic Space. Number 639 in Lecture Notes in Computer Science. Springer-Verlag, Berlin (1992) 348–367
22. Hillier, B.: The hidden geometry of deformed grids: or, why space syntax works, when it looks as though it shouldn't. Environment and Planning B: Planning and Design **26** (1999) 169–191
23. Turner, A., Doxa, M., O'Sullivan, D., Penn, A.: From isovists to visibility graphs: a methodology for the analysis of architectural space. Environment and Planning B: Planning and Design **28** (2001) 103–121
24. Turner, A.: Depthmap: a program to perform visibility graph analysis. In: Proceedings of the Third International Space Syntax Symposium, Atlanta, GA, Georgia Institute of Technology (2001) 31.1–31.9

25. Hillier, B.: A theory of the city as object. Urban Design International **7** (2002) 153–179
26. Norris, J.R.: Markov Chains. Cambridge University Press, Cambridge (1997)
27. Batty, M., Tinkler, K.J.: Symmetric structure in spatial and social processes. Environment and Planning B: Planning and Design **6** (1979) 3–28
28. Turner, A.: Angular analysis. In: Proceedings of the Third International Space Syntax Symposium, Atlanta, GA, Georgia Institute of Technology (2001) 30.1–30.11
29. Dalton, N.: Fractional configuration analysis and a solution to the Manhattan Problem. In: Proceedings of the Third International Space Syntax Symposium, Atlanta, GA, Georgia Institute of Technology (2001) 26.1–26.13
30. Dalton, N.: Storing directionality in axial lines using complex node depths. In: Proceedings of the Fourth International Space Syntax Symposium, London, University College London (2003) 63.1–63.10
31. Winter, S.: Modeling costs of turns in route planning. GeoInformatica **6** (2002) 345–360
32. Dalton, N., Peponis, J., Conroy Dalton, R.: To tame a TIGER one has to know its nature: Extending weighted angular integration analysis to the description of GIS road-centerline data for large scale urban analysis. In: Proceedings of the Fourth International Space Syntax Symposium, London, University College London (2003) 65.1–65.10
33. Asami, Y., Kubat, A.S., Kitagawa, K., Iida, S.: A three-dimensional analysis of the street network in Istanbul: an extension of space syntax using GIS. In Okabe, A., ed.: Islamic Area Studies with Geographical Information Systems. Routledge Curzon, London (2004)
34. Jiang, B., Claramunt, C.: Integration of space syntax into GIS: new perspectives for urban morphology. Transactions in GIS **6** (2002) 295–309
35. Thomson, R.C.: Bending the axial line: smoothly continuous road centre-line segments as a basis for road network analysis. In: Proceedings of the Fourth International SpaceSyntax Symposium, London, University College London (2003) 50.1–50.10
36. Porta, S., Crucitti, P., Latora, V.: The network analysis of urban streets: a dual approach. Available online at `http://arXiv.org/abs/cond-mat/0411241` (2004)
37. Rosvall, M., Trusina, A., Minnhagen, P., Sneppen, K.: Networks and cities: An information perspective. Physical Review Letters **94** (2005) 028701
38. Sabidussi, G.: The centrality index of a graph. Psychometrika **31** (1966) 581–603
39. Freeman, L.C.: A set of measures of centrality based on betweenness. Sociometry **40** (1977) 35–41