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USING QUALITATIVE DISTANCE METRICS IN SPACE SYNTAX AND CONFIGURATIONAL ANALYSES

MICHAEL J. FRITH
Department of Security and Crime Science, UCL, London, United Kingdom
michael.frith.09@ucl.ac.uk

ABSTRACT

One interesting result from space syntactic and graph theoretic configurational analyses are their ability to correlate with pedestrian and vehicular movement flows. These analyses function by representing the built environment as a graph of interconnected spaces. Network centrality measures, such as betweenness, closeness and choice, are then applied to quantify each space's role in the network and, in this case, suggest the potential amount of movement. That said, because these three network measures are based on the calculation of shortest routes and attempt to model human movement, they should incorporate how we judge distances. In traditional space syntax distance is measured by the angular change accrued at junctions along a route and elsewhere it is often measured as the physical length of the route. However, and hitherto incorporated in these analyses, given the limitations of human cognition (e.g. Simon 1979), there must be some constraint to the cognitive precision of this spatial information. This idea of cognitive spatial imprecision is not new (e.g. Dutta 1988; see also Montello 2007) and a number of qualitative models have been produced that attempt to describe or emulate human spatial judgements. For example, Montello and Frank (1996) used simulations to test the ability of angular models to emulate real-life angle estimations, including an eight 45° cone model where angles are approximated to the nearest 45°. For qualitative physical distance the research is less developed however, for instance, Hernández et al. (1995) gives examples of metric distances being split into three, four or five categories. Based on this, the present study tests variations of qualitative angular and physical distance metrics by comparing their ability in network analyses to correlate with data on 409 pedestrian and 297 vehicular count observations in central London. The results indicate qualitative metrics can increase the correlation between network measures and movement flows. More specifically, angular qualitative metrics significantly improved a number of correlations between the network measures and pedestrian movement. For example, the eight 45° cone model improved the correlation for angular choice analyses of axial segments from 0.55 to 0.60. However, the tested qualitative metrics rarely or not at all (significantly) improved the correlations between angular analyses and vehicular movement and between metric network analyses and both types of movement. Reasons for these results are discussed with suggestions for future research.

KEYWORDS

Qualitative Metrics, Space Syntax, Graph Theory, Movement Flows, Distance

1. CONFIGURATIONAL ANALYSES AND DISTANCE

One interesting result from space syntactic and graph theoretic configurational analyses are their ability to correlate with pedestrian and vehicular movement flows. Although more comprehensive descriptions can be found elsewhere (e.g. Hillier & Hanson, 1984), these analyses function by partitioning the built environment into graphs of inter-connected spaces. In traditional space syntax these spaces are defined using axial lines which represent vista spaces and are the fewest and longest hand-drawn straight lines of inter-accessibility passing throughout the urban form (Hillier & Hanson, 1984); or using axial segments where these lines are broken where they intersect other lines (Dalton, 2001; Turner, 2001) and so represent sections of axial lines between two intersections. In other configurational analyses, spaces are derived using street centreline data and in the first case using street segments which are sections of the street network between intersections and/or street end-points. These street segments can also be merged, for example, into named streets (Jiang & Claramunt, 2004) where neighbouring street segments share the same street name and so each space can be described as being semantically distinct. Measures of network centrality, particularly betweenness, closeness and choice (see also Table 1 for definitions and example interpretations of each), are then calculated to quantify each spaces' role within the network and can be used to suggest the potential amounts of movement in each space.

As these three network measures are based on the calculation of the shortest paths through the network, they rely on accurately evaluating distance. That is, since the measures are attempting to model human movement, this distance should relate to cognitive distance and how we comprehend the cost of travel between places (Canter & Tagg, 1975). Originally, space syntax defined this topologically where the distance between spaces is the number of steps (spaces) that must be traversed. For axial line (and somewhat named street) analyses, these steps can be interpreted as changes in direction; as (directly) onward travel is along the same space so no distance is accrued whereas any non (directly) onward travel is to a different space. However, with axial and street segments, onward travel beyond an intersection is to another space so a topological step is always accrued (see also segment problem later). In this case, it is essentially counting the number of intersections. This difference is not trivial as it bifurcates the literature which has focused on the correlation between distance and turnings and generally found encouraging evidence (Bugmann & Coventry, 2005, 2008; Hutcheson & Wedell, 2009; Jansen-Osmann & Berendt, 2002; Sadalla & Magel, 1980). That said, other studies have found mixed (Jansen-Osmann & Wiedenbauer, 2004, 2006) and unfavourable (Briggs, 1973; Herman et al., 1986) results. This can be compared to the studies which consider and find a relationship between distance and the number of intersections (Sadalla & Staplin, 1980b; for an exception see Nasar, 1983; see also Sadalla & Staplin, 1980a).

The validity of topological distance is also questioned due to other wayfinding research. That is, until the late 1990s the long-dominant framework (Montello, 1998) of spatial microgenesis by Siegel and White (1975) posited that spatial knowledge develops in distinct stages including from topological (e.g. knowledge of the topological layout and relationships) to topographical (e.g. knowledge of metric distances and/or relative angular directions). Given this, and that spatial knowledge appears to develop over a year (Evans, 1980) but our primary routes are determined quickly (Rogers 1970, cited in Golledge, 1999), it appeared likely routes are topologically determined. However, as identified by Montello (1998), the idea of longitudinal and sequential spatial knowledge stages is contrary to much research. For example, in relatively recent research (e.g. Brunyé & Taylor, 2008; Foo et al., 2005; Herman et al., 1987; Holding & Holding, 1989; Ishikawa & Montello, 2006; Klatzky et al., 1990; Loomis et al., 1993; Montello & Pick Jr, 1993; Ruddle et al., 2011) it is shown that we can synthesise topographic information relatively instantaneously and this can be concurrent with or before acquiring topological knowledge. As such, models of human wayfinding should incorporate topographic detail.

Although largely independent to the above research, and in fact partly proposed to overcome the segment problem, space syntax introduced angular distance (Turner, 2000; Dalton, 2001; Turner, 2001). Here, the distance between two spaces is the sum of the angular change at intersections along the route. In this way it broadly follows from topological distance and the same research except that it recognises that turnings of different magnitudes can be comprehended (Sadalla & Montello, 1989). It also remedies the segment problem where in axial segment and (to some degree) street segment topological analyses where a linear space is broken into its constituent segments, there is a step cost between each discretised segment.

That is despite those segments being linearly-connected and no true turning being made. In contrast, using angular distance, linearly-connected segments cost nothing to transfer between as the deviation angle is 0° and approximately linearly-segments cost proportional to the change in angle (see also Turner, 2001, 2007).

Although less commonly used and arguably underutilised in configurational analyses (Montello, 2007), distance can also be defined metrically where the distance between two spaces is the physical length of the route. While studies suggest features such as turns (see earlier) can distort the relationship between the actual metric distance and the cognitive distance and that this relationship may be linear (Cadwallader, 1973; Day, 1976; Howard et al., 1973), non-linear (Briggs, 1973; Sherman et al., 1979) or either (Canter & Tagg, 1975; Wiest & Bell, 1985); they are often strongly correlated with coefficients above 0.80 (MacEachren, 1980) and 0.90 (Cadwallader, 1973; Canter & Tagg, 1975; Howard et al., 1973).

Network centrality measure	Mathematical definition	Example interpretation
Betweenness	The number of shortest paths between all spaces that pass through the focal space.	The through-movement potential of a space or how likely a space is to be visited on trips through the network.
Closeness	The inverse of the mean shortest distances from the focal space to all other spaces.	The to-movement potential of a space or how easy a space is to navigate to from all other spaces.
Choice (Normalised Angular Choice)	The betweenness of the focal space divided by its distance from all other spaces	The combination of the through- and to-movement potential of a space or how likely a space is to be visited on trips through the network normalised for how easy it is to navigate to.

Table 1 - Mathematical definitions and example interpretations of the three main network centrality measures used for correlating with movement flows

Sources: Freeman (1977; 1979); Hillier (2005); Hillier et al. (2007).

Support for metric distance can also be found in other research that corroborates turns-based distance as regardless of the number of turns, longer paths are (still correctly) often recalled as longer than the shorter paths (e.g. Hutcheson & Wedell, 2009; Jansen-Osmann & Wiedenbauer, 2006).

2. QUALITATIVE DISTANCE

All this being said, given the limited capacity of human cognition in terms of sensing, encoding, storing into memory and retrieving and recoding from memory (e.g. see Simon, 1979), there must be some constraint to the precision of spatial information that is comprehended. This is especially likely for topographical information (such as angles or distance) as it is infinitely precise. For example, consider Figure 1 and the axial line map in 1a; and the same map with all lines removed that do not contribute to the plausible shortest paths between 'Buckingham Palace' (A) and 'Downing Street' (I) in 1b. Is the angular change in the turning from F to H (95°) discernibly greater to that from H to I (92°)? Or is the length of the segment from the intersection of D-F to F-H (276m) discernibly greater to that from F-H to H-I (240m)? Also, is the route from A to I via B, E and G (which is 386° and 1.7km long) discernibly shorter or longer than the route via C, D, F and H (which is 376° and 1.4km long)?

This idea of cognitive spatial imprecision is not new (e.g. Dutta, 1988). Nor has it yet been proposed for space syntax and similar analyses (Montello, 2007). In terms of the cognitive discernibility of angles at-least, methods to incorporate this using qualitative representations of distances are reasonably well developed (Montello & Frank, 1996). In qualitative representations of distance, also called qualitative distance metrics, distance is measured using qualitative ordinal classes (see below) whereas in the standard approach, which can be called quantitative representations of distance, distance is measured on an absolute ratio scale (e.g. the number of metres or degree of angular change). For example, based on experiments in Sadalla and Montello (1989) where participants estimated the angle sizes of turns they walked, Montello and Frank (1996) used computer simulations to evaluate two models of human angle estimations: a 4-cone model where angles are approximated to the nearest 90° and an 8-cone model where they are approximated to the nearest 45° (see also Figure 2c and 2d respectively). Though these models lacked a strong theoretical a priori, and the cone boundaries may idiosyncratically and aggregately differ (e.g. Franklin & Tversky, 1990; Klippel & Montello, 2007), the results nonetheless highlighted their viability as models of spatial angular perception.

In comparison, there has been less research on qualitative models of metric distance. Frank (1991) briefly suggests distance could be modelled with two (near and far) or three (near, intermediate and far) categories. Fisher and Orf (1991) considered the former of these with distances around a university campus but found the categories were interpreted idiosyncratically. Whilst Hernández et al. (1995) gave the examples of three (close, medium and far), four (very close, close, far and very far) and five (very close, close, commensurate, far and very far) categories. Whilst not explicitly explored in these studies, one issue for metric distance models is whether the total journey length that should be categorised or each segments' length. Here, and notwithstanding the lack of direct empirical evidence, the latter is tentatively suggested as a number of studies (Allen, 1981; Allen & Kirasic, 1985; see also Berendo & Jansen-Osmann, 1997) identify the role of intermediary segments and a relationship between route segmentation and route length estimates.

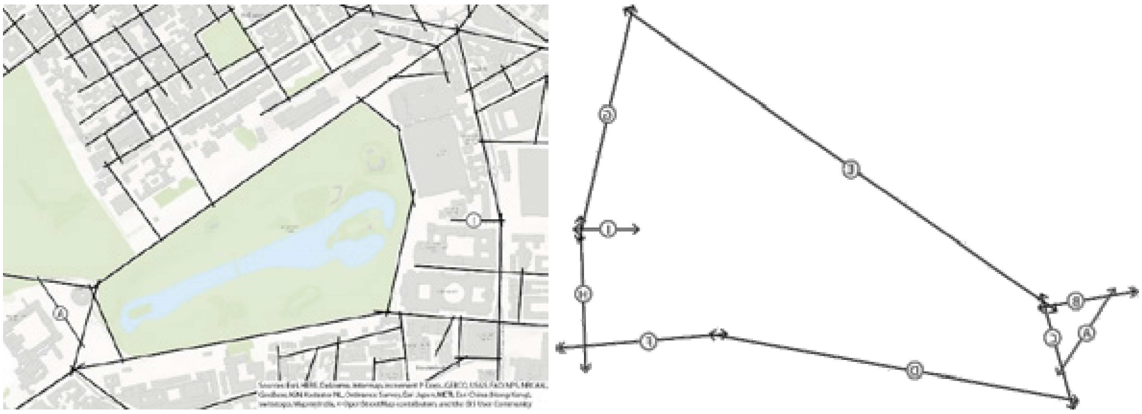

Figure 1 - Axial line maps showing the street network between 'Buckingham Palace' (A) and 'Downing Street' (I) (1a); and with all lines that are extraneous for calculating the plausible shortest path(s) (using angular and metric impedances) between these landmarks removed (1b)

3. THIS STUDY

Based on this research, this study proposes to extend the space syntactic and graph theoretic literature by testing qualitative topographical (angular and metric) distance models. That is, by comparing network measures using quantitative (the approach hitherto in these analyses) and qualitative angular and metric distances in their ability to correlate with pedestrian and vehicular movement flows. This will be conducted by taking angular and metric distances and categorising them into homogenously-sized classes which differ in size for each model. That is where the size of the class relates to the level of precision that turnings are perceived. As shown in Figure 2 for an individual facing the dashed line, for angular distance these include cone sizes of 15° (a 13-way directional change model); 30° (a 7-way directional change model), 45° (a 5-way directional change model) and 90° (a 3-way directional change model)[1]. From this, in terms of the qualitative angular models it is expected:

> ***Hypothesis 1:*** The correlation between network measures and movement will be significantly stronger in angular analyses using qualitative distance than quantitative distance.

Also, although the intention is to test the 3-way and 5-way angular models from Montello and Frank (1996), the 7-way and 13-way models are included for comparison and it is expected:

> ***Hypothesis 2:*** The correlation between network measures and movement will be significantly stronger in angular analyses using 5-way and 3-way qualitative distance models than the 13-way and 7-way distance models.

Based on the results in Montello and Frank (1996) (see earlier), it is also expected:

> ***Hypothesis 3:*** The correlation between network measures and movement will be significantly stronger in angular analyses using 5-way qualitative distance models than 3-way distance models.

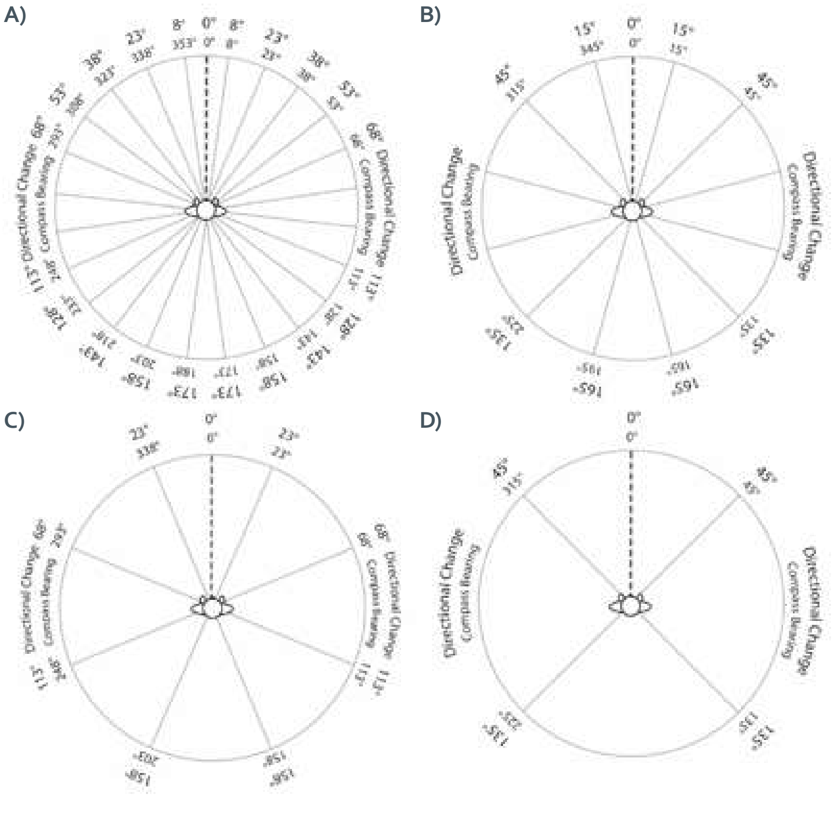

Figure 2 - The 15°-class 13-way (a), 30°-class 7-way (b), 45°-class 5-way (c) and 90°-class 3-way (d) qualitative angular models

1 It is worth noting that unlike the analyses in Montello and Frank (1996), configurational analyses only consider absolute directional changes and so do not distinguish between left and right turnings. For example, the 3-way directional change model (as described in this paper) has directional change classes of 0°-45°, 45°-135°, 135-180° (see also Figure 2D). In comparison, in Montello and Frank (1996) the same model would be described as a 4 90° cone size model (where the cones are 315° - 45°, 45°-135°, 135°-225° and 225°-315°). In this way, the models tested in these analyses are equivalent to those described in Montello and Frank (1996) as 24 cone (the 13-way model), 12 cone (the 7-way model), 8 cone (the 5-way model) and 4 cone (the 3-way model) models.

For metric distance, and in lieu of strong a priori knowledge, four models with class sizes with intervals of 25m, 50m, 100m and 250m are tentatively tested. Here it is anticipated that:

Hypothesis 4: The correlation between network measures and movement will be significantly stronger in the metric analyses that use qualitative distance than quantitative distance.

Furthermore, although no hypotheses are explicitly made it is tentatively anticipated that the qualitative metric models with the largest intervals (e.g. 250m) and the smallest intervals (e.g. 25m) will yield weaker correlation coefficients than the other models (those with 50m and 100m intervals). This is reasoned because these models are likely to represent distance judgements too coarsely or too finely respectively.

4. METHODOLOGY

To test these models and their ability to correlate with movement flows, 409 pedestrian and 297 vehicular count observations in central London are taken from two datasets. The first dataset, as originally used in Penn et al. (1998), includes 312 pedestrian and 233 vehicular count observations from Barnsbury, Clerkenwell and Kensington. The second, as used in Penn et al. (1998; see also Chang & Penn, 1997, 1998), includes 98 pedestrian and 64 vehicular count observations from South Bank. Note that the first dataset, as provided, is missing 58 observations which are omitted for various reasons (Iida, 2006) whilst a further nine pedestrian and two vehicular observations are omitted because they could not be georeferenced for all street network representations. From the second dataset, 10 pedestrian and three vehicular observations are also omitted because they could not be georeferenced for all street network representations. These data regard the average number of 'moving adults' or 'moving vehicles' observed in each space per hour.

Pedestrian and vehicular graphs for each of the street network representations described earlier (street segment, named street, axial line and axial segment) were generated from Ordnance Survey network data. This includes where the axial line (and axial segment) graphs were hand-drawn following the space syntax methodology (for example see Al-Sayed et al., 2014). Each graph is then analysed using the common graph theoretic measures of betweenness and closeness and the space syntax measure, (normalised angular) choice[2] (see also Table 1). Based on similar use within the literature and the results from a meta-analysis (Frith et al., 2016) these measures are calculated using radii (to ignore distant spaces that should have no influence on the properties of each space from the measure calculations) of 2000m for the pedestrian analyses and 5000m for the vehicular analyses. These were all computed using a program written in Python by the authors of this paper.

Unlike similar analyses in this literature, the Kendall Tau-a rank correlation coefficient (τ) is used to quantify the correlation between these data. This is because in most studies it is found there is a non-linear relationship between these variables. As such, to use the popular Pearson's r correlation coefficient would require one of any number of data transformations. In comparison, the τ statistic only considers the relative ranks of the data and because those data transformations do not change the order of the data, they are redundant as they will not affect the correlation. The τ coefficient can be interpreted as the probability that for any two pairs of metric (X) and observation (Y) data that $X_j - X_i$ and $Y_j - Y_i$ are concordant and share the same or opposite signs. The values range from -1 if all combinations of pairs possess different signs (i.e. there is a negative relationship), 0 if there is perfect discordance and each sign is equally likely and 1 if they all possess the same sign (i.e. there is a positive relationship). That said, because τ coefficients appear smaller in magnitude compared to other indices such as Pearson's r, Greiner's relation is used to calculate and show the approximate equivalent r values (Kendall, 1949).

2 Note that as briefly alluded to the possibility of in Hillier et al. (2007), the betweenness-choice normalisation procedure used to calculate (normalised angular) choice - typically used for angular analyses of axial segment - is also used to create choice measures for angular analyses of networks built from the other units (axial lines, street segments and named streets) and for metric analyses of all four types of networks.

The correlation coefficients are computed using the somersd package (Newson, 2014) in Stata (StataCorp, 2015). To test the hypotheses, the correlation coefficients are compared using Wald tests (using the lincom command also in Stata) which determine if they differ significantly (i.e. that one model is a better estimator of movement and so has a higher correlation coefficient than the other model). Also, because multiple comparisons are necessary for some hypothesis, for example in hypothesis 1 where four qualitative angular models are compared to the quantitative angular model, multiplicity and the increased likelihood of incorrectly rejecting the null hypothesis is controlled using the Bonferroni correction.

5. RESULTS

For parsimony, Tables 2 and 3 summarise the results and show the estimated correlation coefficients between movement flows and angular (Table 2) and metric (Table 3) analyses using quantitative distance and the top correlating equivalent analysis using qualitative distance. The correlation results for all (qualitative distance) analyses can be found in Tables 4-7 in the appendix.

Regarding hypothesis 1, and as shown in Table 2, the results indicate that incorporating qualitative angular metrics in network analyses can increase their correlation with movement flows. In the case of correlating with pedestrian movement, for five of the 12 analyses (combinations of network type and network measure) the correlations were significantly greater when using (at-least one model of) qualitative distance compared to when using quantitative distance. The largest increases are between pedestrian movement and closeness which increases from 0.33 to 0.52 for street segment analyses and from 0.36 to 0.51 for named street analyses; both using the 3-way model. Other notable significant increases include betweenness analyses of axial segments when using the 5–way model (0.53 to 0.57); choice analyses of axial lines when using the 3-way (0.52 to 0.56) and 5-way (0.52 to 0.55) models and choice analyses of axial segments when using the 5-way model (0.55 to 0.60).

Network Measure	Network Type	Pedestrian Movement		Vehicular Movement	
		Quantitative Distance	Qualitative Distance	Quantitative Distance	Qualitative Distance
Betweenness	Axial Line	0.50	0.51†	0.80	0.79
	Axial Segment	0.53	0.57**	0.83	0.81
	Street Segment	0.41	0.37	0.84	0.81
	Named Street	0.34	0.35†	0.82	0.77
Closeness	Axial Line	0.71	0.71†	0.71	0.72†
	Axial Segment	0.66	0.66†	0.68	0.72†
	Street Segment	0.33	0.52**	0.71	0.73†
	Named Street	0.36	0.51**	0.67	0.71*
Choice	Axial Line	0.52	0.56*	0.80	0.80
	Axial Segment	0.55	0.60**	0.83	0.81
	Street Segment	0.40	0.37	0.84	0.82
	Named Street	0.34	0.37†	0.82	0.79

† indicates the qualitative model correlates better but not significantly than the equivalent quantitative model and * and ** indicates the qualitative model correlates significantly better at $p<0.05$ and $p<0.01$ levels respectively.

Table 2 - Correlations between pedestrian and vehicular movement and angular network analyses using quantitative and the top correlating analysis using qualitative distance

In comparison, when correlating with vehicular movement only one analysis correlates significantly more strongly when using qualitative distance rather than quantitative distance. In this analysis, closeness analyses of named streets, the correlation increases from 0.67 to 0.71 with the 7-way qualitative distance model. That said, in a further three (compared to a further five in the pedestrian analyses) analyses, closeness analyses of the other network types, the correlation coefficient increases, but not significantly, when using (at-least one of) the qualitative distance models.

While this compares the angular qualitative models to the equivalent quantitative models, the qualitative models can also be compared to each other to determine which correlate best with movement. For hypothesis 2, in terms of pedestrian movement the correlations for the top correlating 3-way or 5-way model is significantly greater than that for the top correlating 7-way or 13-way model for six analyses (betweenness analyses of axial segments and named streets; closeness analyses of street segments and named streets; and choice analyses of axial segments and named streets). For five analyses (those except closeness analyses of axial lines) the top correlating 3-way or 5-way analysis is still greater but not significantly. In comparison, for vehicular movement the 7-way or 13-way models best correlate in all analyses, including significantly in three analyses (betweenness analyses of street segments; closeness analyses of street segments and choice analyses of street segments).

When comparing just the 3-way and 5-way models for hypothesis 3, the correlations for both types of movement tend to be greater in the 5-way model than the 3-way model. More specifically, the correlation with pedestrian movement using the 5-way model is significantly greater than that with the 3-way model in five analyses (all betweenness analyses and choice analyses of named streets) compared to in two types of analyses for the reverse (closeness analyses of street segments and named streets). For vehicular movement the correlations are significantly greater using the 5-way model of distance for four analyses (betweenness analyses of named streets and closeness analyses of axial lines, axial segments and named streets) while in no analyses is the correlation using the 3-way model significantly than that using the 5-way model.

Network Measure	Network Type	Pedestrian Movement		Vehicular Movement	
		Quantitative Distance	Qualitative Distance	Quantitative Distance	Qualitative Distance
Betweenness	Axial Line	0.45	0.46†	0.71	0.65
	Axial Segment	0.52	0.42	0.77	0.68
	Street Segment	0.34	0.37†	0.80	0.69
	Named Street	0.33	0.34†	0.81	0.63
Closeness	Axial Line	-0.03	-0.11**	0.26	0.19
	Axial Segment	0.01	0.12**	0.40	0.34
	Street Segment	0.05	0.03	0.42	0.33
	Named Street	0.04	-0.04	0.40	0.32
Choice	Axial Line	0.45	0.46†	0.72	0.65
	Axial Segment	0.51	0.41	0.78	0.68
	Street Segment	0.33	0.37†	0.80	0.63
	Named Street	0.31	0.33†	0.81	0.69

† indicates the qualitative model correlates better but not significantly than the equivalent quantitative model and * and ** indicates the qualitative model correlates significantly better at $p<0.05$ and $p<0.01$ levels respectively.

Table 3 - Correlations between pedestrian and vehicular movement and metric network analyses using quantitative and the top correlating analysis using qualitative distance

Regarding hypothesis 4, as shown in Table 3 the results indicate that the qualitative metric distance models do not consistently and significantly increase the correlation with movement compared to the equivalent analyses using quantitative distance. For pedestrian movement two analyses significantly increase in strength when using (at least one model of) qualitative distance compared to when using quantitative distance. These are closeness analyses of axial lines and axial segments which increased from -0.03 to -0.11 and from 0.01 to -0.12 respectively. That said, in six of the remaining 10 types of analyses the correlations increased, but not significantly, when using at-least one model of qualitative distance. These are betweenness and choice analyses of axial lines, street segments and named streets. In comparison, for vehicular movement none of the analyses using qualitative metric distance correlated more strongly (significantly or not significantly) than the equivalent analysis using quantitative distance.

Additionally, and although no explicit hypotheses were made, the correlations for the qualitative metric distance models can also be compared to each other. This includes where it was tentatively expected that the analyses using metric intervals of 50m or 100m would correlate with movement more strongly than those using intervals of 25m or 250m. For pedestrian movement this expectation was supported as the correlation for the top correlating 50m or 100m model was significantly stronger in five of the types of analyses and stronger but not significantly in six of the remaining seven analyses. That said, the results indicate the top correlating models were those with intervals of 25m and 50m, and when these are compared, the analyses using the 50m qualitative distance model correlated more strongly in all analyses except closeness analyses of street segments and this was significant in five of the types of analyses (betweenness analyses of street segments and named streets; closeness analyses of axial segments and choice analyses of street segments and named streets). For vehicular movement the top correlating models were always those using 25m or 50m intervals and when these are compared (which is the same as comparing the top correlating analysis using 25m or 250m intervals to the top correlating analysis using 50m or 100m intervals) the correlations for analyses using 25m intervals were significantly stronger in two analyses (closeness analyses of street segments and named streets) and stronger but not significantly in six of the remaining analyses.

6. DISCUSSION

In this paper novel qualitative models of angular and metric distance were used to test their effect on the ability of network measures to correlate with pedestrian and vehicular movement flows. That is where it was anticipated that network analyses that incorporate qualitative models - and so are likely to better approximate human spatial reasoning - will more strongly correlate with movement than the equivalent non-qualitative (quantitative) analyses. The results from this paper partially support this expectation and indicate that the tested qualitative models of distance can significantly increase the strength of the correlation with movement flows. In other words, qualitative models of distance can improve the ability of network measures to estimate the amount of movement in a space.

More specifically, the results highlighted that when using qualitative angular models of distance, network measures correlated more strongly with pedestrian movement in five of the 12 tested types of analyses. That said, the practical importance of these increases can be examined as the largest increases are found in two of the formerly worst correlating types of analyses (closeness analyses of street segment and named street network representations). Moreover, the overall top correlating model (which uses the 7-way qualitative model of angular distances and closeness analyses of axial lines) does not correlate substantially or significantly more than that of the equivalent quantitative analysis. For qualitative angular analyses of vehicular movement and qualitative metric analyses of pedestrian movement the results are more mixed. In the analyses where the qualitative models correlate more strongly than the equivalent quantitative models, the differences are generally not significant or substantial and the (improved) qualitative-based correlation is notably smaller than that of a quantitative-based correlation for another types of analysis. The tested qualitative models of metric distance did not improve any of the correlations between network measures and vehicular movement.

That said, the possible viability of qualitative models is suggested by the results for hypotheses 2 and 3. That is where the models (used in this paper) found to best emulate real-life angle estimations in Montello and Frank (1996), the 3-way and particularly the 5-way qualitative angular models, tended to correlate more strongly with pedestrian movement than the other qualitative models. Also, and while the 5-way model also correlated with vehicular movement more strongly than the 3-way model, the discrepancy whereby the 7-way and 13-way models overall best correlated with vehicular movement may be explained by the research from which Montello and Frank (1996) is based on, Sadalla and Montello (1989). That is where this research involved participants walking a path and estimating the angular change of direction rather than driving. As such, the qualitative models tested in Montello and Frank (1996) which serve as the basis for those used in this analysis are conceivably calibrated to pedestrian spatial cognition rather than vehicular. This is something future research may consider and particularly if such research considers more sophisticated variants of qualitative metrics such as those also used in Montello and Frank (1996) but were beyond the scope of this paper. Similarly, the mixed results found for the qualitative metric distance models may be somewhat attributable to the general lack of research into this topic whereby the intervals tested in this paper were largely conjectured without strong a priori evidence. This is again something future research may want to consider.

Beyond these issues, it is important to acknowledge other limitations associated with these analyses. The most important limitation is that these results regard one set of analyses using data from just one city. Here, and especially salient as this analysis (of the use of qualitative distant metrics in configurational analyses) is as far as the authors are aware the first of its kind, it is unknown if the results generalise to other locations or even to other data from the same location (London). This issue may also be exacerbated as some of data used in these analyses (the first dataset) were non-randomly missing data-points. For example, six data-points were excluded as they concern cul-de-sacs and therefore do not generate through movement (Iida, 2006). In this way and although these exclusions may have little effect on the correlation results, they may also have substantial effects whereby the results are only generalisable to alike locations. Future research is needed to test this and the replicability of these findings. Given the early stage of this avenue of research, future studies may also want to expand on the types of analyses compared. That is, these analyses only considered limited network centrality measures and representations of the street network. For example, future research may also want to test qualitative distance metrics in more recent analyses including those using alternative network measures such as the PageRank measure (e.g. Jiang, 2006; Jiang, Zhao, & Yin, 2008) or weighted analyses where each space is weighted in the network measure calculations by some measure of its importance or attractiveness as a destination and/or origin (e.g. Karimi, Parham, & Acharya, 2015; Turner, 2007). Lastly, and while the correlation results presented are approximately of the same magnitude as Pearson's values (which are commonly used in similar analyses), it must be reiterated that these are derived from Kendall Tau-a correlation coefficients and should be interpreted as such (including in terms of their benefits over Pearson's correlation coefficients; see earlier).

To summarise, this paper is the first of its kind to test the use of qualitative distance metrics in configurational analyses for their impact on the ability to correlate with pedestrian and vehicular movement. Although the results provide mixed support for qualitative distance metrics, in light of its novelty, future research is suggested to elaborate on these findings and to test other variants of these qualitative metrics.

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APPENDIX

Network Measure	Network Type	Quantitative Model	Angular Qualitative Models			
			3-way	5-way	7-way	13-way
Betweenness	Axial Line	0.50	0.48	0.51†	0.50	0.49
	Axial Segment	0.53	0.51	0.57**	0.53†	0.49
	Street Segment	0.41	0.33	0.37	0.35	0.35
	Named Street	0.34	0.26	0.35†	0.31	0.31
Closeness	Axial Line	0.71	0.68	0.69	0.71†	0.69
	Axial Segment	0.66	0.63	0.66†	0.63	0.64
	Street Segment	0.33	0.52**	0.35†	0.33	0.34†
	Named Street	0.36	0.51**	0.41*	0.42**	0.41**
Choice	Axial Line	0.52	0.56*	0.55*	0.54†	0.52†
	Axial Segment	0.55	0.59†	0.60**	0.55†	0.51
	Street Segment	0.40	0.37	0.37	0.35	0.35
	Named Street	0.34	0.33	0.37†	0.32	0.33

† indicates the qualitative model correlates better but not significantly than the equivalent quantitative model and * and ** indicates the qualitative model correlates significantly better at p<0.05 and p<0.01 levels respectively.

Table 4 - Correlations between pedestrian movement and angular network analyses using quantitative and qualitative distance

Network Measure	Network Type	Quantitative Model	Angular Qualitative Models			
			3-way	5-way	7-way	13-way
Betweenness	Axial Line	0.80	0.76	0.78	0.79	0.79
	Axial Segment	0.83	0.78	0.80	0.81	0.80
	Street Segment	0.84	0.74	0.75	0.77	0.81
	Named Street	0.82	0.73	0.77	0.77	0.76
Closeness	Axial Line	0.71	0.60	0.69	0.71	0.72†
	Axial Segment	0.68	0.61	0.70†	0.72†	0.68†
	Street Segment	0.71	0.64	0.68	0.69	0.73†
	Named Street	0.67	0.60	0.68†	0.71*	0.64
Choice	Axial Line	0.80	0.77	0.78	0.79	0.80
	Axial Segment	0.83	0.77	0.80	0.81	0.80
	Street Segment	0.84	0.77	0.76	0.78	0.82
	Named Street	0.82	0.78	0.78	0.79	0.77

† indicates the qualitative model correlates better but not significantly than the equivalent quantitative model and * and ** indicates the qualitative model correlates significantly better at p<0.05 and p<0.01 levels respectively.

Table 5 - Correlations between vehicular movement and angular network analyses using quantitative and qualitative distance

Network Measure	Network Type	Quantitative Model	Angular Qualitative Models			
			3-way	5-way	7-way	13-way
Betweenness	Axial Line	0.45	0.41	0.46†	0.37	0.28
	Axial Segment	0.52	0.41	0.42	0.26	0.24
	Street Segment	0.34	0.26	0.37†	0.22	0.11
	Named Street	0.33	0.24	0.34†	0.23	0.16
Closeness	Axial Line	-0.03	-0.07**	-0.11**	-0.06†	-0.07†
	Axial Segment	0.01	-0.06**	-0.12**	-0.06†	-0.07†
	Street Segment	0.05	0.03	0.00	-0.02	0.01
	Named Street	0.04	0.00	0.02	-0.04	0.01
Choice	Axial Line	0.45	0.41	0.46†	0.37	0.28
	Axial Segment	0.51	0.40	0.41	0.25	0.23
	Street Segment	0.33	0.25	0.37†	0.21	0.10
	Named Street	0.31	0.23	0.33†	0.22	0.15

† indicates the qualitative model correlates better but not significantly than the equivalent quantitative model and * and ** indicates the qualitative model correlates significantly better at $p<0.05$ and $p<0.01$ levels respectively.

Table 6 - Correlations between pedestrian movement and metric network analyses using quantitative and qualitative distance

Network Measure	Network Type	Quantitative Model	Angular Qualitative Models			
			3-way	5-way	7-way	13-way
Betweenness	Axial Line	0.71	0.64	0.65	0.57	0.54
	Axial Segment	0.77	0.68	0.65	0.54	0.52
	Street Segment	0.80	0.68	0.69	0.62	0.59
	Named Street	0.81	0.63	0.59	0.51	0.45
Closeness	Axial Line	0.26	0.16	0.19	0.07	0.14
	Axial Segment	0.40	0.34	0.28	0.06	0.13
	Street Segment	0.42	0.33	0.21	0.07	0.24
	Named Street	0.40	0.32	0.17	0.05	0.20
Choice	Axial Line	0.72	0.65	0.65	0.58	0.55
	Axial Segment	0.78	0.68	0.65	0.54	0.52
	Street Segment	0.80	0.63	0.59	0.50	0.45
	Named Street	0.81	0.69	0.68	0.62	0.59

† indicates the qualitative model correlates better but not significantly than the equivalent quantitative model and * and ** indicates the qualitative model correlates significantly better at $p<0.05$ and $p<0.01$ levels respectively.

Table 7 - Correlations between vehicular movement and metric network analyses using quantitative and qualitative distance