Scaling of Geographic Space and its Implications

Position paper by Bin Jiang

Department of Technology and Built Environment, Division of Geomatics, University of Gävle, SE-801 76 Gävle, Sweden, Email: bin.jiang@hig.se, Web: http://fromto.hig.se/~bjg/

Geographic space is a large-scale space that is beyond the human body, and cannot be perceived from a single viewpoint. It complements to small-scale spaces that is viewable entirely from a single viewpoint (Mark and Frank 1996). The large-scale geographic space consists of numerous perceivable objects or small-scale spaces. The size of the numerous perceivable objects or small-scale spaces bears a scaling property. This scaling property, sometimes called fractal or scale invariance, says simply that small perceived objects or spaces are extremely common, while large ones are very rare – the improbable. Or put it differently, the size of the perceivable ones is very diverse, which bears a power law distribution. What is the power law distribution then? Formally, the power law distribution is expressed by $P(x) \sim x^{-\alpha}$, where x is a quantity that measures the occurrence of some phenomena, α is so called power law exponent. What we are most familiar with is probably Gaussian distribution or normal distribution. Basically, normal distribution says that events vary around an average, so the size of the event is predictable. This is in contrast to power law distribution, in which an average makes little sense, and variance is unpredictable. In terms of height, there is an average man around 1.7 meters, but not an average city. Or there is indeed an average city size, but it makes little sense. In other words, unlike human height which is normally distributed, city size is power law distributed or follows Zipf's law (Zipf 1949).

Any geographic space that is reasonably large enough would bear this scaling property. Taking urban street networks for example, the length and connectivity of individual streets have the scaling property. It can be expressed by the 80/20 principle, i.e., 80% of streets are short or less connected to about four other streets, while 20% of streets are long or well connected to more than four other streets. Interestingly within the 20%, there are less than 1% of streets that are extremely long and extremely well connected to many other streets. This scaling pattern is universal for small, large and middle sized cities, for US cities and European cities, and for the cities from elsewhere (Jiang 2007). The finding of scaling is mainly from the perspective of individual streets: their length and connectivity – a nonplanar graph perspective. On the other hand, if we consider a street network as a planar graph, and concentrate on the individual cellular spaces enclosed by streets such as facilities, residences, parks or blocks, the size of the cellular spaces bears a striking power law distribution as well (Lämmer, Gehlsen and Helbing 2006). The scaling property of geographic space is in line with the early endeavors on fractal cities (Batty and Longley 1994), although a different perspective in terms of the investigation.

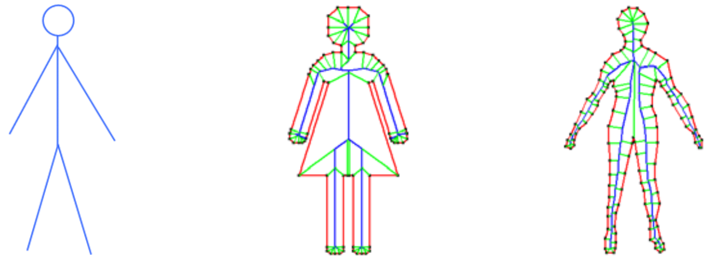
In what follows, I will speculate on implications of this scaling property from three perspectives: human movement patterns, human mental maps (internal representation) and geographic representation (external representation). First of all, the scaling of geographic space has a direct impact or influence on human movement patterns - human flow aggregated to individual streets. This has been investigated from both observation and simulation (Jiang 2009, Jiang, Yin and Zhao 2009, Jiang and Jia 2010). It is found that (1) aggregate flow is predictable just by looking at the underlying space structure which exhibits power law feature; (2) aggregate flow is power law distributed, implying that a minority of streets account for a majority of traffic. The scaling of human movement patterns is also confirmed by other studies (Gonzalez, Hidalgo and Barabási 2008, Brockmann, Hufnage and Geisel 2006), although none of the studies examined the underlying mechanism of the scaling. Earlier efforts led by Hillier and his colleagues (Hillier et al. 1993, Hillier 1996) concentrated on the correlation between spatial configuration and human movement flow, but never the scaling property. It is important to note that the human movement patterns we refer to are at an aggregate or collective level.

How much individual movement is influenced by the fractal geographic space is still an open question.

The second implication of the scaling is to do with mental maps or internal representation. I believe that the scaling of geographic space is the reason the image of the city (Lynch 1960) can be formed in our minds. A needle can be found in a haystack is because the needle is extremely rare in a haystack, and it forms a distinguished landmark. This is also the reason the Google search engine can efficiently and effectively find what we search for. On the basis of network thinking, Google built up and continue to update a huge web graph in terms of which web page is hotlinked which other pages. The number of the hotlinks of web pages tends to be scaling. It is this scaling that makes the Google search engine effectively find what we search for. The Google search engine relies on PageRank (Brin and Page 1998) to rank all individual pages, and those distinguished stand at the top of the list. In this regard, the Google search engine captures those landmarks from a webscape the same way as human minds capture those prominent city elements from a cityscape.

The third implication refers to external representation or geographic representation. Conventionally, both raster and vector built on field/object theory are two representation models implemented in GIS software. Simply speaking, geographic representation is to represent or partition a large-scale geographic space into numerous small pieces, e.g., squared cells in raster and individual objects in vector. However, these representations are computer models rather than human models. For example, while looking at an image, our minds capture individual objects rather than pixels. In this regard, the vector model seems better than the raster one, but adjacency relationship in the vector model is not obvious, and it must be based on the computation of line-line intersection. Due to the limitation of the raster/vector models, Gold (1992) suggested an alternative Voronoi spatial model that he believes is closer to a human model of space. In fact, the Voronoi spatial model is not without a problem.

To make our point clear, let's take a look at a human figure to think of how human minds perceive it internally and in the mean time to see how it is represented by a computer model. We have no neurological evidence, but we can make some common sense reasoning. I believe that no one, even the kids still in a kindergarten, would deny Figure 1a shows a human figure that consists of a head, two arms and two legs linking to the main body. This concise yet informative drawing captures fairly well the essential configuration of the human beings. On the other hand, let's look at how a computer model would represent a human figure. A Voronoi spatial model based on Blum's medial axis (Blum 1967) can extract the skeleton of a human being by following precisely medial points of the shape. However, the resulting skeletons (blue lines with Figure 1b and 1c) differ substantially between symmetric and asymmetric human figures. The two computer generated skeletons appear very different from the human generated one as shown in Figure 1a. This difference is mainly attributed to the sensitivity of medial axis, i.e., a slight change in the shape can lead to a dramatic change in the skeleton (*c.f.* Figure 2 for an illustration). I believe that many people can imagine a human figure from the human-drawn skeleton shown in Figure 1a, probably a very few could do the same imagination from the computer generated skeletons in Figure 1b and 1c. Furthermore, I believe that for the rectangle shape in Figure 2, a line simply stretched in the middle of the shape would be sufficient to capture the essence of the simple configuration.



(a) (b) (c)

Figure 1: Human model versus computer model: (a) human-drawn skeleton of a human figure, (b) medial axes of a symmetric human figure, (c) medial axes of an asymmetric human figure

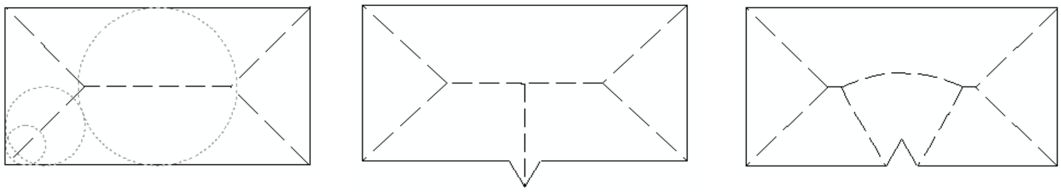


Figure 2: Illustration of Blum's medial axes and their sensitivity (After Jiang and Liu 2010a)

From the above elaboration, it seems clear that human minds do not conduct a precise computation as a computer does to derive the skeleton of a shape. Instead human minds can pattern recognize those essential parts of a shape – the parts that have semantic or practical meaning. This gives us inspiration to think of geographic representation or think of how to represent a large-scale geographic space into perceivable small-scale spaces or pieces. The key point here is that the perceivable small-scale spaces must hold some semantic or practical meaning. The pixels in the raster model have no such meaning, and the medial axes make little sense due to the above mentioned sensitivity. We will see in the following that the objects in the vector model sometimes make little sense as well. For an effective geographic representation, important thing is whether or not it is represented into pieces that capture the parts that we perceive. As argued elsewhere (Jiang and Liu 2010a), an axial map consisting of the least number of longest visibility lines seems a better alternative than the medial axes. This is because that the axial lines rather than the medial axes capture what we perceive. Figure 2 demonstrates some typical street patterns, where every axial line represents one small-scale space individually. All the axial lines together, or the corresponding axial map as a whole, constitutes an image of the urban environment – a very few long lines (indicated by red) intersected by many short ones (by other colors). This is exactly the kind of scaling embedded in geographic space and further reflected in our mental maps.

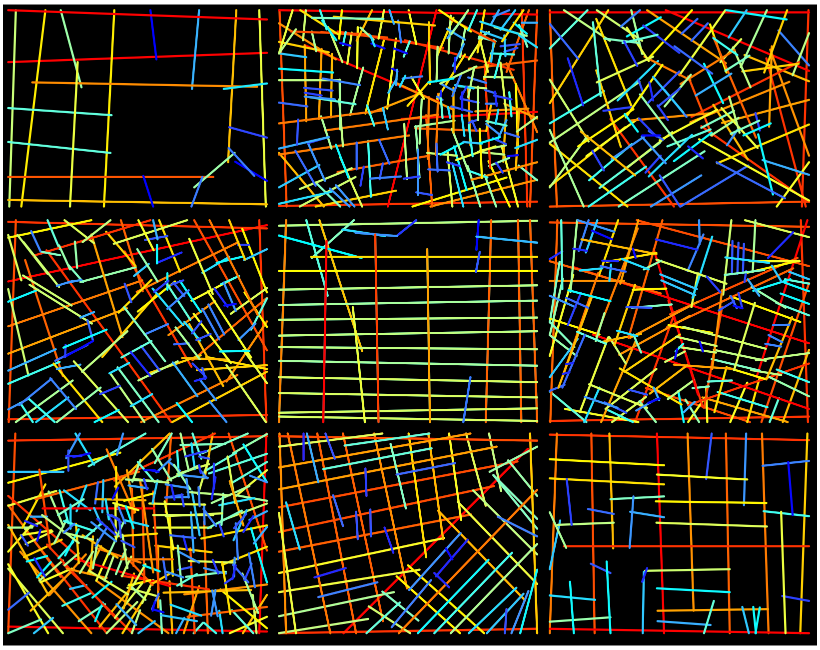


Figure 3: A set of axial maps that capture what we perceived about urban environments (After Jiang and Liu 2010a)

It appears that the objects in the vector model represent truly what we perceive, but it is not completely true. For example, a road network is represented as a graph in which nodes and links represent respectively road junctions and road segments. Although human minds can pattern recognize individual roads from a road map, we "see" only adjacency relationships of segments or junctions from the graph. This representation deviates from human perception or a human model in which roads are perceived as meaningful units often given by unique names – so called named streets (Jiang and Claramunt 2004). This is at a semantic level. At a perceptual level, human minds tend to form what is called self-organized natural roads (Jiang, Zhao and Yin 2008). A graph consisting of nodes representing the individual roads and links if the corresponding roads intersected suggests a better (geographic) representation of road networks. This graph is often called connectivity graph which bears no geometric attributes yet is purely topological in nature. The traditional representation or graph based on connectivity of road junctions or segments is still much geometry oriented in the sense that (1) each junction has a geometric location; (2) each road segment bears a geometric distance. This traditional representation dominates many network oriented analysis and computation, e.g., in deriving the shortest paths. It is an effective model for some tasks or operations like routing and tracking in current transport networks modeling. However, human beings conceptualize a route in a rather different way. We think of the connectivity of roads rather than road segments while planning a route. Starting from this, we have developed a novel approach to computing fewest-turn routes based on the connectivity of natural roads, combining geometric, semantic and topological information together for map directions (Jiang and Liu 2010b). It is found that the derived fewest-turn routes are not only shorter but also with fewer turns than the simplest paths (Duckham and Kulik 2003, Mark 1985) or Google Maps' routes. From this development, we see a clear advantage of the connectivity graph over the traditional segment-based representation.

The scaling of geographic space reflects a kind of spatial heterogeneity that can be characterized by the power law distribution. However, traditional spatial heterogeneity is mainly described by the normal distribution (Anselin 2006). Goodchild (2004) noted power law like spatial heterogeneity, but he did not believe that space can be infinite as time. Eventually he denied the existence of power law like spatial heterogeneity. This is the key difference between the scaling of geographic space and the spatial heterogeneity in the conventional sense. Furthermore, the larger the geographic space, the clearer the scaling, I believe. Someone may argue that it is a matter of scale, i.e., to what extent or scale you investigate geographic space, a district, a neighborhood, a city, a state, a region or the entire globe. It is indeed true that spatial extent matters in the assessment of scaling or spatial heterogeneity. But my point is that up to a reasonable large scale, say, city or town scale (sometimes even down to the neighborhood scale) the scaling would be striking enough. From the perspective of statistical physics, normal distribution is often called even distribution because of the variation around an average. A geographic space with the normal distribution (or without scaling) tends to be boring because of a lack of changes or variances, and it is therefore hard to form an image in our minds. I tend to believe that the scaling reflects a true picture of geographic space, while the traditional spatial heterogeneity characterizes only partial truth, just as only half-truth about an elephant is revealed in the minds of blind men. Nowadays, data intensive computing provides an important tool to assess the scaling nature of geographic space at a massive data scale. Scaling should be considered a true 'normal' distribution rather than an outlier or anomaly in dealing with geographic space.

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