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Analysing the relations between spatial structures and action patterns

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The thematic framework of this contribution is the general assumption that where we can find stable spatial structures, the related action-patterns are also stable and vice versa (Franck 2002). Cities are permanent as spatial structures because they contain action-patterns with extraordinary stable rhythms. The classification of processes according to the degree of the stability of their rhythms is suitable as a new and promising attempt to characterize the effects of changing structures.

This paper proposes a research method to examine this complex interplay of spatial structures and action-patterns. We introduce cellular automata and agent-based models to simulate abstract mechanisms as simply as possible. These basic simulation models can be used as a kind of building blocks to find answers for more complex questions. Our intention is to propose a virtual laboratory to investigate spatial processes and analyse the results visually with the help of graphic output from simulation programs.

'What constitutes an explanation of an observed social phenomenon? Perhaps one day people will interpret the question, "Can you explain it?" as asking "Can you grow it?"' (Epstein and Axtell 1996)

Keywords: Spatial processes; Action patterns; Urban modeling and simulation; Cellular automata; Agent-based systems

1. Buliding blocks

The general strategy to build up a complex system by combining separate building blocks follows the examples of Herbert Simon's (1981) architecture of complexity and the ideas of John Holland (1998). To construct basic simulation models in the context of geographic systems, geosimulation (Benenson and Torrens, 2004) provides relatively new simulation techniques such as cellular automata (CA) and multi agent systems (MAS), which allow urban theory to be modelled. CA and MAS models offer a number of important innovations: They are disaggregated and interactions can be simulated between individuals and building units. The algorithms that they use can be derived directly from theoretical ideas of how cities work and they are often displayed as visual environments. This makes them a lot easier to interpret and analyse than pure mathematical models.

For the development of complex urban simulation models, the design of each single model or building block must be undertaken in such a way that they can be combined with each other. Therefore, the first step is to introduce a standardized convention for describing models based on mathematical formalizations. For this purpose we will draw upon the standardized format introduced by König and Bauriedel (2006). In a second step we describe the individual building blocks and in a third step we combine the models introduced so far to examine if more complex simulation can produce more significant results.

2. Spatial structures

The first two models deal with the generation of spatial structures. These models were chosen because they can generate abstract fractal structures, and this is a very important feature of human settlements. The fractal geometry of spaces which make other spaces accessible and of spaces made accessible through other spaces can be considered as a self-organizing system. Starting with the smallest architectonic entity – the single room – the built structure appears as a sequence of accessed spatial units and accessing space around. The room is accessible from the corridor, the apartment from the staircase, the staircase from the site utilization, the building plot from the service road, the quarter from the highway etc.

2.1 Diffusion connect model

The first building block is the diffusion connect model (Batty 2005, p. 50) and is very similar to a diffusion limited aggregation system. Like all the following models, this one is based on a cellular raster space. Here we use a 133 x 133 cell grid, where each cell is addressed by the letter *i, j* or *k*. In addition, a given number *M* of free agents A^m, $m = 1, 2, \ldots, M$ are spread randomly across the cellular field:

$$A_j^m = random(j) \qquad (2.1)$$

The mathematical formalization for the random movement of the agents A^m at each time interval t can be written as:

$$A_k^m(t) = \text{move } \{A_j^m(t-1),\ \text{random}(\Phi),\ \text{random}(d)\} \qquad (2.2)$$

where Φ is the angle variation of the agents heading and d is the distance to travel. After each time interval t we check whether there are more agents in the local neighbourhood than the global threshold value ψ states. If this is the case, then the corresponding cells will be developed and the respective agents settle down:

$$if \sum_{k \in \Omega i} A_k^m(t) > \psi \text{ then } D_i(t) = 1, \text{ otherwise } D_i(t) = 0 \qquad (2.3)$$

To define neighbourhood we use the Moore-Neighbourhood Ω_i which considers the 8 cells *k* which surround a central cell in a 3x3 cell grid.

In verbal terms these mathematical formulae describe how agents move randomly across a cellular field until they find an attractive place where they can settle. Attractiveness is equated with the level of activity at a location. The activity in turn is measured by the agents in the local neighbourhood. Thus, when there are enough agents in a neighbourhood, they settle down and end their wanderings.

The basic parameter for the system development is the threshold value, which describes the number of agents that are necessary to make a location attractive for a settlement. By increasing this threshold value, the amount of evolving cluster reduces because it is harder for the agents to find a satisfactory place to settle. An increase in the entire numbers of agents in the system leads to more and larger emerging clusters. Four different growth structures are shown in figure 1. The way the structures evolve in this model can be considered as analogous to the attracting forces of cities.

The simulation program is available as executable windows file (exe) from the URL: http://www.entwurfsforschung.de/Strukturfor/delphi/delphiF.htm#Diffusion-Connect

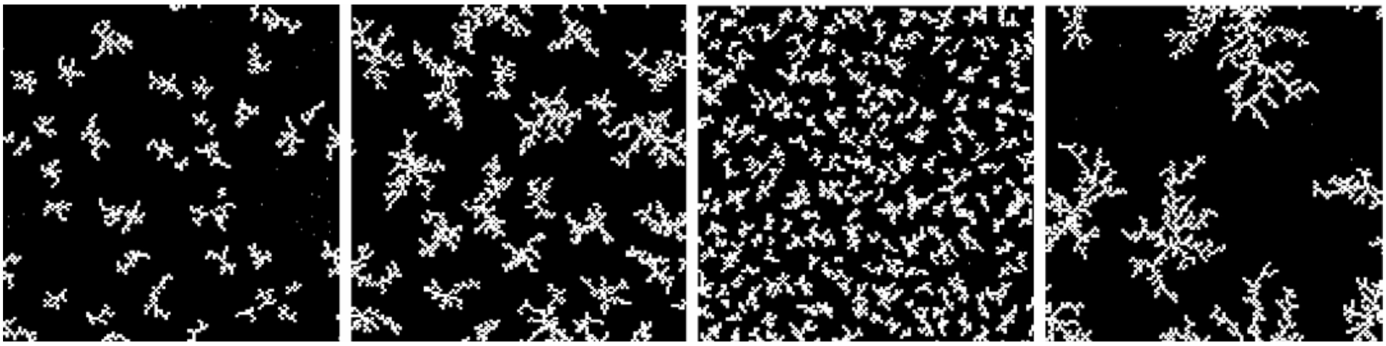


Figure 1: Results with different settings for the threshold value ψ and the number of agents M in the system. From left to right: a) $\psi = 4$, $M = 1000$; b) $\psi = 6$, $M = 2000$; c) $\psi = 4$, $M = 3000$ and d) $\psi = 7$, $M = 1500$

2.2 Growth in a potential field

Compared to the previous model, which examined the accumulating process of an existing amount of elements, this model deals with the growth of structures by adding new elements to the system (Batty 2005, p. 122-131). We don't actually need to add real new objects, but represent a new element by changing the state D of a cell at location i from not developed 0 to developed 1.
In the beginning, all 101 x 101 cells in the field have the state 0; only the cell c in the grid centre has the state 1. To determine which cells shall be developed during the process, we introduce a potential property P for each cell. The start conditions are as follows:

$$P_i(0) = \sum_{k \subset \Omega i,\ k \neq i} P_k(0)/4, \quad D_c(0)=1, \quad D_i(0) = 0, \quad \forall\ i \neq c. \tag{2.4}$$

In this case we use the von Neumann-Neighbourhood Ω_i, which considers the 4 directly adjacent cells k (to the north, east, south and west) to the central cell in a 3x3 cell grid.
With each time interval t one cell will be developed, where the potential value P_i is highest when an already developed cell is in the von Neumann-Neighbourhood. To avoid symmetric growth we add a random noise value ε_i. Thus, the transition rule can be written as:

$$\left\{ \begin{array}{l} \text{if } \sum\limits_{k \subset \Omega,\ k \neq i} D_k(t) \geq 1 \text{ and } P_i(t) + \varepsilon_i(t) = \max \\ \text{then } D_i(t+1) = 1 \text{ and } P_i(t+1) = 0 \end{array} \right\} \tag{2.5}$$

Together, the potential values P_i form a field called a diffusion field. It is shown by the grey gradient in figure 02. In each time interval the diffusion field is brought to an approximated equilibrium by calculating the field several times (in this example five times per time step):

$$P_i(t+1) = \sum_{k \in \Omega i,\ k \neq i} P_k(t+1)/4 \text{ where } D_i(t+1) = 0. \tag{2.6}$$

Around a given distance to the growing cluster, its 'sphere of influence', all potentials are equal to 1. Thus, as one gets further from the cluster, there is a greater probability or potential that the cell might be developed.

$$P_i(t) = 1 \quad \text{where} \quad r_c > R_{\max} + \tau, \tag{2.7}$$

where R_{max} is the edge cell of the cluster and τ is the distance to the sphere of influence.
Using this model we can simulate a growth process through the interaction of potential values. After a location has been development, the surrounding places have a relative low potential for further development

because equation (2.5) sets the potential of a developed cell to 0 and this low value ‘diffuses’ to the adjacent cells. Some time is needed until the potential increases again – we can interpret this as the fulfilment of needs in this area for the moment and no further development is required. The sphere of influence is responsible for a higher probability of cluster growth at the edge than in the centre. However, if we increase the noise value, this effect is reduced and more dense structures evolve such as those in figure 2d. Thus, the most important parameters for the system’s evolution are the noise value and the size of the sphere of influence. The simulation program is also available as executable windows file (exe) from the URL: http://www.entwurfsforschung.de/Strukturfor/delphi/delphiF.htm#diffuseGrowth

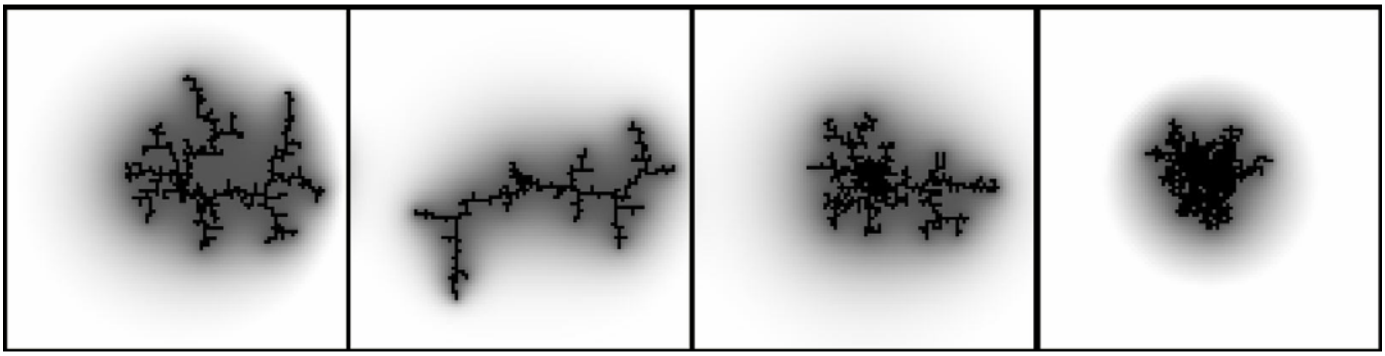


Figure 2: The diffusion field is shown by the grey gradient, where the white cells are the ones with the highest potential values P_{max} = 1 and the middle gray cells are the ones with the lowest values. The developed cells are marked black. From left to right: a) $\varepsilon_i = 5$, $\tau = 5$, at $t = 500$; b) $\varepsilon_i = 2$; $\tau = 10$, at $t = 300$; c) $\varepsilon_i = 5$, $\tau = 20$, at $t = 500$; d) $\varepsilon_i = 20$, $\tau = 10$, at $t = 500$.

3. Action patterns

So far, we have been concerned only with the generation of abstract spatial structures. Now let us look to the related action patterns that are associated with settlements. Analogous to the spatial fractal structure of the transportation system, a fractal time structure of the usage of this system can be detected: A person walks around the room so and so often before stepping out into the hallway; a person walks around the flat so and so often before departing; a person covers so and so many ways there and ways back within the quarter before visit a surrounding district; a person drives around in the home town so and so often before visiting an other city etc. Together, these oscillating movements form a hierarchy of again self similar rhythms and are often typical stable processes. They trace back to the starting point and tend towards an equilibrium. The sum of such movements of an urban actor in a particular period of time can be represented as a ‘trace’ or trajectory, the spatial expansion of which represents the action space of an actor.
To build a model based upon the description above is a very complex task. Accordingly, the two models we introduce in this section are only a first approach.

3.1 Interaction patterns

With the interaction pattern model we can generate a dynamic pattern that reflects the actions of individual agents that influence the actions of following agents (Batty 2005, p. 226-234). An analogy is that of ants in an ant colony exploring the environment for food (Resnick 1997). This basic mechanism can be adapted to reflect more complex processes in cities as we will discuss in this and the next section.

For this model we have used a cellular field with 201 x 201 cells in which ten randomly placed resources R_i are located. In addition, in the middle of the field the origin cells O_i for the agents are located. In the beginning 800 agents A_m^k are placed on this origin. The cellular field is used as an abstract landscape that is completely empty $\{T_m(0) = 0\}$ when the process starts. We use this landscape to track the movement of the agents. In the beginning the agents explore the landscape in a random way until they find a resource. During this time the agents are in 'exploration mode', which is indicated by the direction of the arrow above the letter *A*. When moving, an agent responds to the trails established by previous agents by following the gradient of the trail landscape $\{T_i(t)\}$:

$$\overrightarrow{A_m^k}(t+1) = \max_i \left\{ \nabla T_i(t), \varepsilon_i^k(t) \right\} \tag{3.1}$$

When the trail landscape is still empty or the values for $T_i(t)$ in all adjacent cells are equal, a random error ε_i^k determines the direction of movement. When an agent encounters a resource *R* at cell *m* the agent changes to 'returning mode':

$$\text{If } \overrightarrow{A_m^k}(t) \Leftrightarrow R_m, \text{ then } \overleftarrow{A_m^k}(t+1) \tag{3.2}$$

When in 'returning mode' on its way back to the origin *i* the agent use a method of navigation that depends on its prior knowledge of the location. We can write this as

$$\overleftarrow{A_m^k}(t+1) \leftarrow \mu\left(O_i, m\right) \tag{3.3}$$

When moving in 'returning mode' the agent leaves a trace on the landscape to mark the way from the resource to the origin. The according landscape rule for the returning agent is:

$$T_m(t+1) = T_m(t) + \varnothing \left\{ \sum_k \overleftarrow{A_m^k}(t) \right\} \tag{3.4}$$

where $\varnothing$ is the strength of the mark an agent leaves at a cell. The entire process begins afresh when the agent encounters its origin and switches once again back into "exploration mode":

$$\text{If } \overleftarrow{A_m^k}(t+1) \Leftrightarrow O_i, \text{ then } \overrightarrow{A_m^k}(t+1) \tag{3.5}$$

The traces in the landscape enable the agents to communicate indirectly with one another. As the process proceeds the agents learn from each other where resources are located and how to find the shortest path to a resource cell. By following paths marked by 'returning' agents, the agents are able to find resources more quickly than by 'stumbling across them'. The different strengths of the traces result in a kind of competition between the traces, with those most effective traces being reinforced whilst others lose their attraction. Figure 03 maps the evolution of direct connections between the origin and the ten resources.

With this model we can measure the interaction rates or streams *F* between the origin and the destinations. The frequency with which agents visit a resource depends on the distance from the origin and the distances from other resources. This leads to more realistic results than the equation of the social physics paradigm where the stream *F* depends only on the size and the distance of two locations:

$$F_{ij} = \left(P_i \bullet P_j\right) / {d_{ij}}^2 \tag{3.6}$$

For example, in the bottom row of figure 3 we can see that if two destinations are located close together, the interaction streams reinforce each other. In general terms we can understand this model as a bottom-up simulation of the top-down social physics paradigm. The simulation program is available as executable windows file (exe) from the URL:

http://www.entwurfsforschung.de/Strukturfor/delphi/delphiF.htm#interactP_01

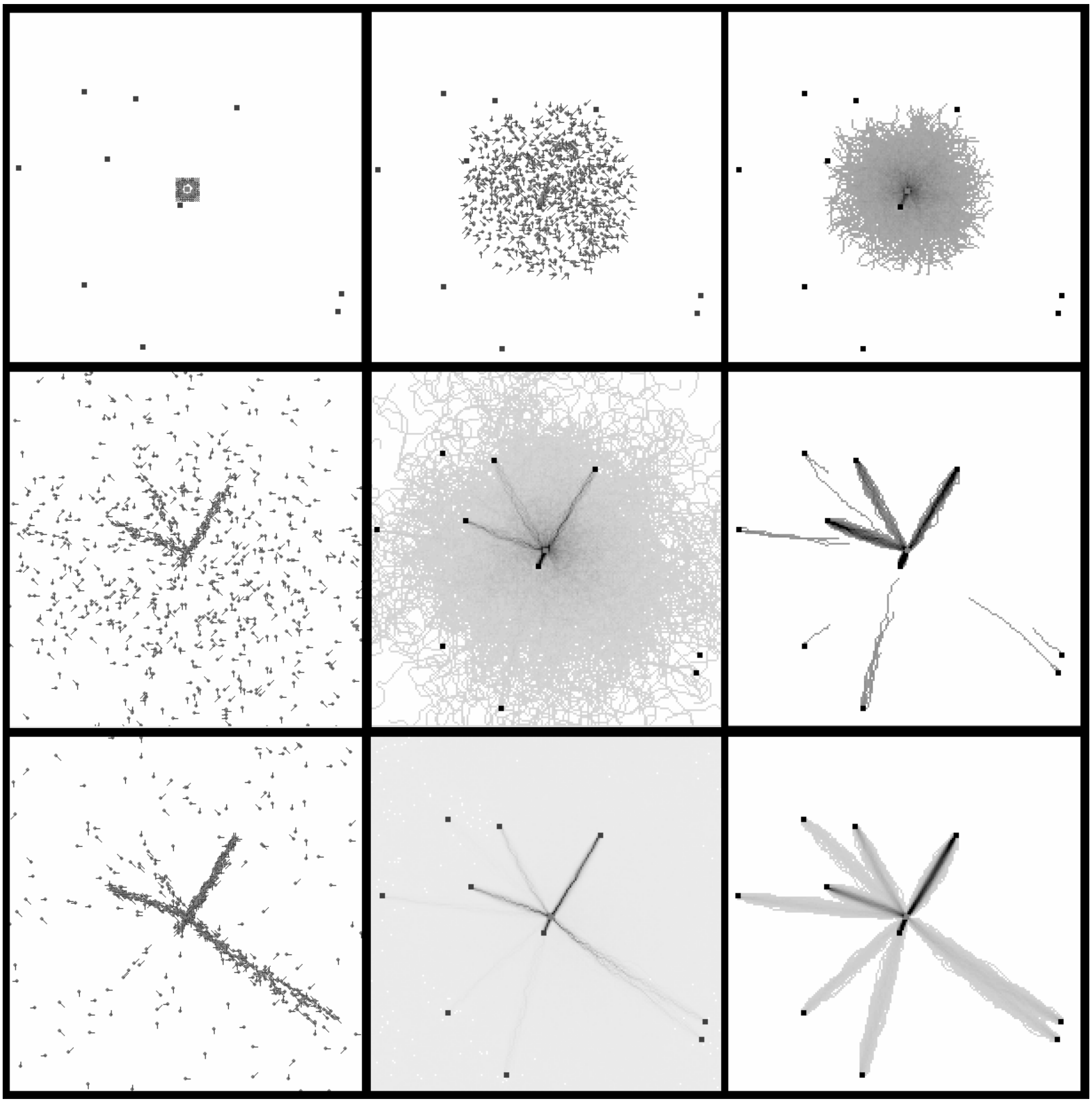


Figure 3: The simulation structure consists of 201 x 201 = 40,401 cells and M = 800 agents in each illustration. Upper row from left to right: a): start configuration with ten random placed resources and the origin in the middle, t = 0; b) actual agents, t = 50; c) all tracks, t = 50; middle row from left to right: d) actual agents, t = 200; e) all tracks, t = 200; f) return tracks, t = 200; bottom row from left to right: g) actual agents, t = 1000; h) all tracks, t = 1000; i) return tracks, t = 1000.

3.2 Path system

The next model demonstrates how the principle mechanism employed in the previous model can be easily adapted with a few changes to generate a more detailed path system. The process we model here is analogous to the trails that evolve when people walk across a freshly snow-covered place. They prefer to use existing trails instead of making a new one, even if a little detour is necessary.

Here we have used a cellular field of 67 x 67 cells and in this example ten origins are randomly scattered across the field with the middle of the field occupied this time by the resource cells. The 200 agents we use in the system are equally distributed to the ten origins. Here, we employ the same concept of an empty landscape $\{T_m(0) = 0\}$ as used for the interaction pattern model. For the exploration mode we have used equation (3.1): as long as the agents have not yet discovered a centre cell or a path mark, they wander randomly across the field. When an agent encounters a resource *R* at cell *m,* the agent changes into 'returning mode', as described in equation (3.2).
However, for this model, the method for the returning mode is changed in the following way. First, the agent directs it's heading *H* towards its origin cell $H \rightarrow O_i$. Each agent has memorised the coordinates of its origin. The heading is calculated by

$$H_A(t+1) = H_A(t) \rightarrow O_i + \text{random}(\omega)\,, \tag{3.7}$$

where ω is the strength of a random wiggle noise. Second, the agent compares the adjacent cells in its range of vision and executes equation (3.1) again. The range of vision can be adjusted by the program parameter 'angle threshold' Φ.
As soon as an agent finds a resource cell, its mode changes and it attempts to return to its origin cell as quickly and effortlessly as possible. On its way back the agent leaves a mark on the cells it crosses. Subsequent agents now attempt to follow these marks on their way home (to save costs). These marks are also used by agents who are still (or again) searching for the resource cells.
The landscape rule from equation (3.4) is extended by the evaporate rate μ for $0 < \mu < 1$:

$$T_m(t+1) = \mu \left[T_m(t) + \varnothing \left\{ \sum_k \overleftarrow{A_m^k}(t) \right\} \right] \tag{3.8}$$

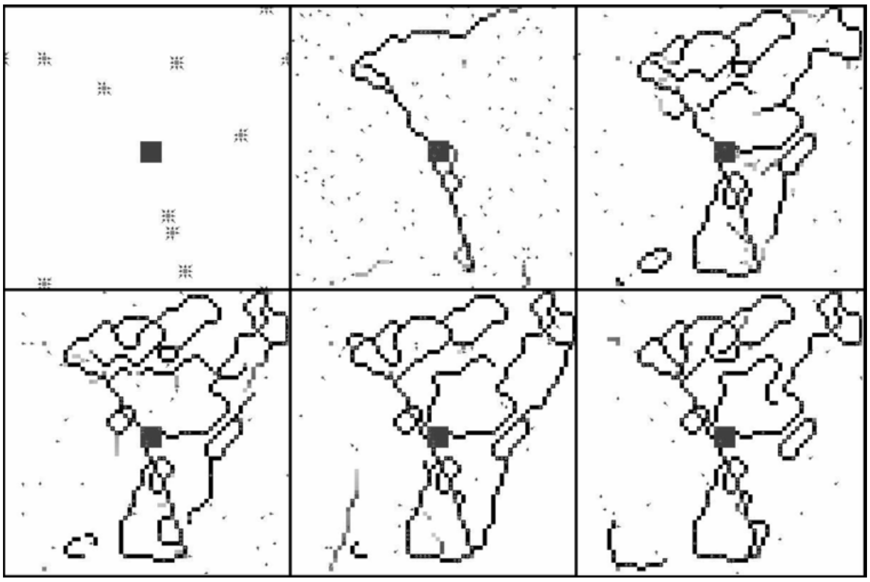


Figure 4: A path system with $M = 200$ agents and 67 x 67 = 4.489 cells with the settings $\Phi = 45°$, $\omega = 25°$, $\varnothing = 50$ and $\mu = 0.5$ at the time steps from above left to below right: $t = 2$, 200, 1.000, 4.000, 10.000, 20.000.

The process begins afresh from the beginning when the agent encounters its origin and switches once again back into exploration mode, see equation (3.5). This variation of the previous model generates natural-looking path systems and the traces are now more differentiated. In figure 4 you can see how a network evolves between the origin and resource cells, whereby the origin cells are often connected directly with each other,

even though they do not always show a direct connection to the central resource. After initial fluctuations a relatively stable path structure evolves which changes only minimally over longer time periods and which is comparatively resistant to disturbances from outside (mouse interaction). The simulation program is available as executable windows file (exe) from the URL:
http://www.entwurfsforschung.de/Strukturfor/delphi/delphiF.htm#path02

4. Interaction and land use

The last model presented in this section combines three of the models introduced previously (2.1 diffusion connect, 2.2 growth in a potential field and 3.1 interaction patterns) and adds some refinements to the process. In this more complex exploration we want to examine the relations between the spatial structure and action patterns that were formed by individual agents in dependence on the land use. At the same time it is important to look at the evolution of the land use pattern as a result of the previously existing spatial structure and the actions generated by the individuals (Batty 2005, p. 241–252).
The simulation structure consists of a 201 x 201 cellular field, where ten randomly placed resources R_i are located. According to the potential field from model 2.2 we introduce a diffusing potential field to this model. Each potential values is a measure of local mass around any location. In general terms the potential is defined as

$$P_i(t+1) = P_i(t) + \theta\nabla^2 P_i(t) + o_i(t) + \varepsilon_i(t), \qquad (4.1)$$

where θ is a diffusion coefficient, $o_i(t)$ is the location of a new spatial element at time t, and $\varepsilon_i(t)$ is an appropriate error term reflecting noise in the distribution. At time $t + 1$, a new spatial element o_m is located at the location with the highest potential value:

$$o_m(t+1) = \max_i \{P_{it}(t)\} \qquad (4.2)$$

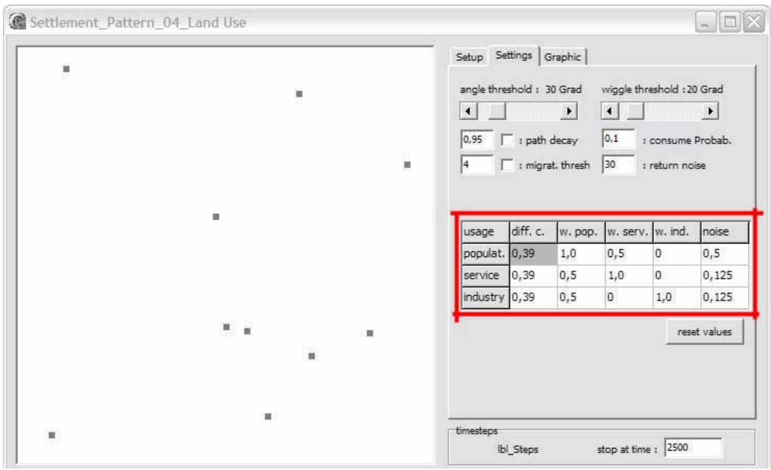
Every new spatial element is the origin for a new single agent. The behaviours for the new agents are the same as those used for the interaction pattern model 3.1. Thus, we can use equations (3.1) – (3.6) to describe the agent's movement and its interaction with the landscape. We also introduce a migration feature following equation (2.3) from model 2.1 that is reformulated here to

$$if \sum_{i\in\Omega m} A_i^k(t) \geq \xi \text{ then } ik \rightarrow mk \qquad (4.3)$$

The operator → means that the agent's initial origin at i is changed to m. This happens, when an agent finds a location with an equal or higher activity than the threshold ζ demands. The activity is measured by the amount of other agents in the Moore-Neighbourhood Ω_m. The process is constrained so that an agent can change its position only once.
This may be sufficient for a basic model for investigating relations between action patterns and spatial structures. However, we want to extend the structure to include the locations of new resources during the process. Thus, in addition to the ten fixed resources we introduce two further resources, manufacturing and service sites as a function of population and of one another and population as a function of all three types of resources. The population is represented by the mobile agents and its origins. The causal structure is that adopted in the most widely used land-use-transportation models first introduced by Lowry (1964).
We now extend the primary potential equation (4.1) by the definition of three potentials – population $\{P_i(t)\}$, manufacturing industry $\{I_i(t)\}$, and services $\{S_i(t)\}$, which we specify as

$$\begin{Bmatrix} P_i(t+1) = P_i(t) + \theta^P \nabla^2 P_i(t) + \sum_A \omega_{iA}^P(t) \cdot o_{iA}(t) + \varepsilon_i^P(t) \\ I_i(t+1) = I_i(t) + \theta^I \nabla^2 I_i(t) + \sum_A \omega_{iA}^I(t) \cdot o_{iA}(t) + \varepsilon_i^I(t) \\ S_i(t+1) = S_i(t) + \theta^S \nabla^2 S_i(t) + \sum_A \omega_{iA}^S(t) \cdot o_{iA}(t) + \varepsilon_i^S(t) \end{Bmatrix} \tag{4.4}$$

where θ^P, θ^I and θ^S are diffusion coefficients for population, industry, and service respectively, $\omega_{iA}^P(t)$, $\omega_{iA}^I(t)$ and $\omega_{iA}^S(t)$ are weights on the importance of the addition of single activity units A to the appropriate potential, and $\varepsilon_i^P(t)$, $\varepsilon_i^I(t)$ and $\varepsilon_i^S(t)$ are the noise terms associated with the process of forming potential. The table in figure 5 shows how the weight set is structured so that for population potential, the weight on population itself is 1 and that on services is 0.5. We have also set the population weights for industry and service potential to 0.5, with the weights for industry on industrial potential and service to service potential equal to 1. All other weights are set to zero. With these settings we use the same configuration as Batty (2005, p 250).



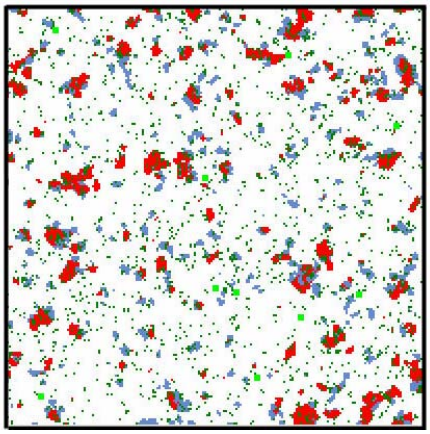


Figure 5: Left: The start configuration of the model with the weight table outlined in red. Right: Generated settlement structure at t = 2,500 (light green = fixed resources, green = population, blue = industry, red = service)

Figure 6 illustrates the results of a process without migration in the upper and middle row and with migration in the bottom row. The chosen noise parameters lead to many relatively small clusters. When we decrease the noise parameters, the resulting patterns show fewer but larger clusters. The picture on the right in figure 05 shows the same pattern as the first two pictures in the first column in figure 06 but with different land uses colour-coded.

The first two rows of figure 06 are generated using the same parameters, but the pictures show the results for different time periods. The upper row illustrates the process at t = 2,500 when the generation of new resources and agents was halted and the middle row at t = 20,000. By comparing the action patterns, visualised by the tracks in the third and fourth column we can see how the connections between the main clusters become clearer when the agents have used the landscape for a longer time.

The graphs in the last column of figure 06 record the average travel time of all agents from their origin to a resource and back again. In the beginning of the process this average value increase rapidly, but as the agents begin to inform the landscape, they ‘learn’ how to find shorter ways to the resources. The curve in the bottom

row falls faster than the one in the first row because here the agents migrate mostly to a location nearer to those resources where activities are usually higher.
To ensure that the agents find not only those resources closest to them, we introduced a probability value. Thus, the agents are able to move through resources without capturing them and search the entire space. In the example shown we have used a probability $p = 0.1$. This is analogous to the real-life behaviour of people who do not necessarily shop or work at markets/workplaces directly near to them. As a result the agents mapped in the pictures in the second column of figure 6 are relatively scattered.

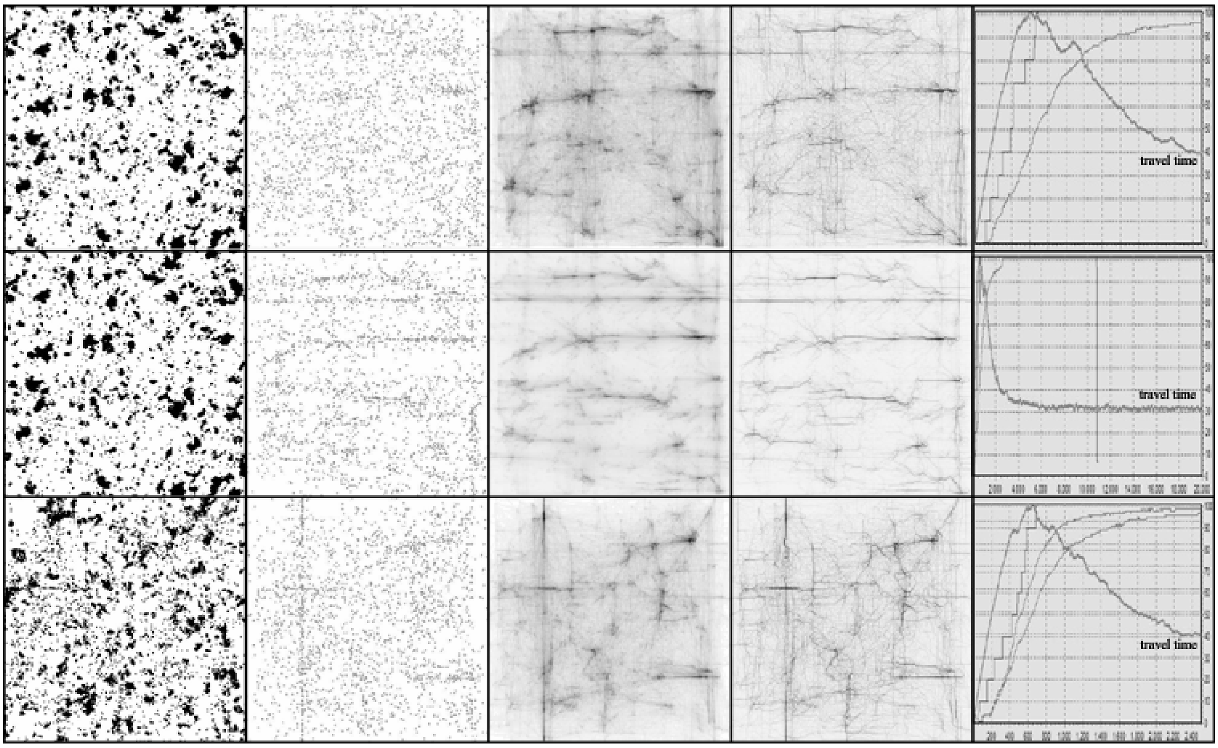


Figure 6: Settlement structures in the upper and middle row generated without migration and in the bottom row with migration. The columns show from left to right a) the land use, b) the positions of the agents, c) the returning tracks, d) all tracks and e) the average travel times.

The possible land use patterns that we can generate with this model are very extensive. In addition to the parameters introduced so far, it is possible to generate any number of agents (population), services and industry in any one time period. In this paper we can present only an extract of the feasible structures. For those wishing to undertake their own experiments using this model, the simulation program is provided as executable windows file (exe) from the website:
http://www.entwurfsforschung.de/Strukturfor/delphi/44_SettlementLandUse.exe

5. Measuring change

'Cities have no central planning commission that solve the problem of purchasing and distributing supplies… How do these cities avoid devastating swings between shortage and glut, year after year, decade after decade? The mystery deepens when we observe the kaleidoscopic nature of large cities. Buyers, sellers, administrations, streets, bridges, and buildings are always changing, so that a city's coherence is somehow

imposed on a perpetual **flux of people** *and* **structures**. *Like the standing wave in front of a rock in a fast-moving stream, a city is a pattern in time.'* – John Holland (2000)

In the language of complexity theory, John Holland's metaphor of the standing wave is called a 'strange attractor'. Such an attractor is a system at the edge of chaos, which does not tend towards an equilibrium point nor slips into chaos, but oscillates between.
To analyze spatial structures at different points in time and temporal structures with different trajectory geometries, we need a method to measure these structures. For this, the classic measure of Shannon entropy (Batty 2005, p. 82), (HUBLER 2001) is a promising approach. This method can be shown with the help of the dynamic development of cellular automata in figure 07.
In a random sequence, all 2^X possible sub-sequences of length X (called correlation length) must occur with equal probability. Deviations from randomness imply unequal probabilities for different sub-sequences. With probability $p_{i,n}$ for the 2^X possible sequences of cell values in a pattern of length X, one may define a spatial metric entropy:
$H = (1/X) \cdot \Sigma_i \, p_{i,n} \cdot \log_2(p_{i,n})$, where $i = 1,2,...,2^X$
The metric entropy is between 0 and 1. With the help of this value one can classify dynamic behaviour in four types [Wolftram 2002]. The graphs in figure 7 show these types from top left to bottom right: monotone, periodical, chaotic and self-organizing. We still have to translate this method to measure the processes in our 2D cellular field.

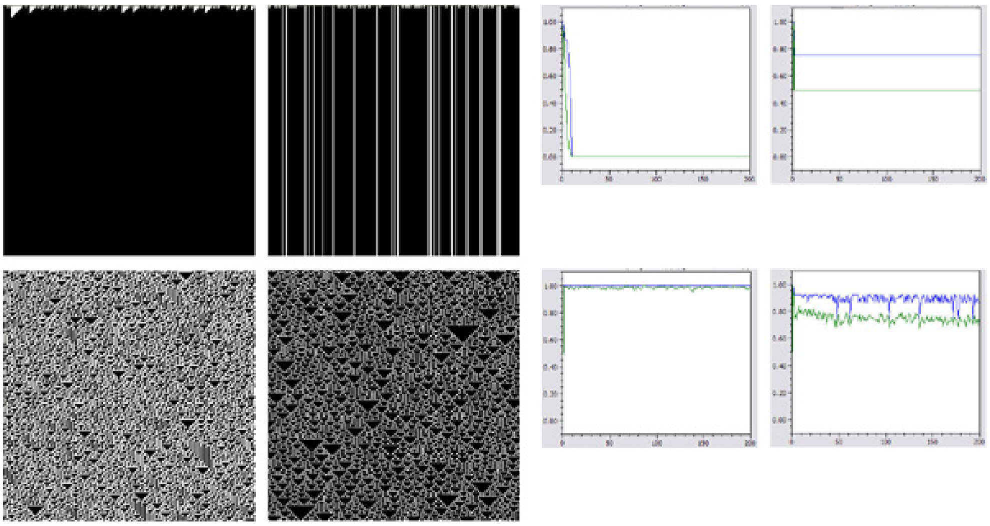


Figure 7: Measure of complexity at different cellular automata

6. Future Prospects

It is obvious that the models presented here are just a first attempt to explore the extensive relationships between the spatial structures of cities and the action patterns they comprise. In future work we want to further examine the following coherences.
To make the urban processes manageable for further investigations, not only the movements of actors shall be recorded by trajectories but also the course of all sorts of processes. The shapes of these trajectories can be illustrated as a four-dimensional (tree space-coordinates and one time-coordinate) 'line', 'tube' or 'tree' (figure 8). An example of a tube-like process is a vehicle, the base area of which remains the same, but the

covered circulation area changes with speed. The standard example of a tree-like process is the history of a plot of land, whose actual shape is determined by multiple mergers and divisions. From the form of the trajectories, activity-patterns can be derived (daily, weekly, seasonally and annual exchange-processes) which allow statements about user-frequencies of spatial units (figure 9) to be made (Hägerstrand 1975). These activity-patterns we can call rhythms. By analysing their form, conclusions can be drawn about their stability (Frank and Wegener 2002). Furthermore the form can be analysed with regard to daily, weekly and annual changes using the measurement method described above.

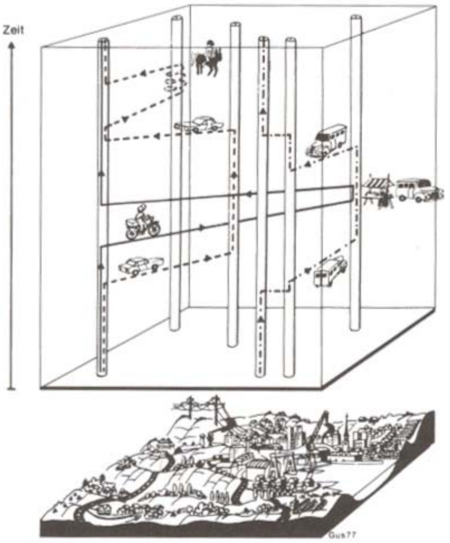


Figure 08: Trajectories
(http://www.ethesis.net/geografie/geografie_deel_I.htm)

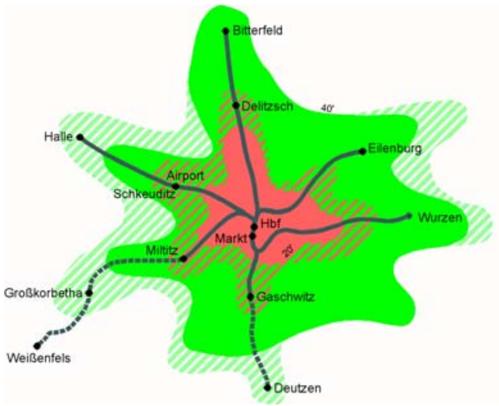


Figure 09: Action Spaces (Hägerstrand 1970)

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The programs the screenshots are taken from are available as prototypes from:
http://www.entwurfsforschung.de/Strukturfor/delphi/delphi.htm

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