

A STUDY ON CELLULAR AUTOMATA BASED ON RELATIONAL DATABASES AND SPATIO – TEMPORAL SIMULATIONS OF CULTURE DIFFUSION

LUO Ping^{1,2}, DU Ding – yun¹, HE Su – fang², LI Sen², MICHAEL Gallagher³, NIU Hui – en³
(1. School of Resources and Environmental Sciences, Wuhan University, Wuhan 430079, P. R. China; 2. Department
of Tourism & Geography, Foshan University, Foshan 528000, P. R. China; 3. Shenzhen Graduate School
of Town Planning, Shenzhen 518031, P. R. China)

ABSTRACT: This paper presents a development of the extended Cellular Automata (CA), based on relational databases (RDB), to model dynamic interactions among spatial objects. The integration of Geographical Information System (GIS) and CA has the great advantage of simulating geographical processes. But standard CA has some restrictions in cellular shape and neighbourhood and neighbour rules, which restrict the CA's ability to simulate complex, real world environments. This paper discusses a cell's spatial relation based on the spatial object's geometrical and non – geometrical characteristics, and extends the cell's neighbour definition, and considers that the cell's neighbour lies in the forms of not only spatial adjacency but also attribute correlation. This paper then puts forward that spatial relations between two different cells can be divided into three types, including spatial adjacency, neighbourhood and complicated separation. Based on traditional ideas, it is impossible to settle CA's restrictions completely. RDB – based CA is an academic experiment, in which some fields are designed to describe the essential information needed to define and select a cell's neighbour. The culture innovation diffusion system has multiple forms of space diffusion and inherited characteristics that the RDB – based CA is capable of simulating more effectively. Finally this paper details a successful case study on the diffusion of fashion wear trends. Compared to the original CA, the RDB – based CA is a more natural and efficient representation of human knowledge over space, and is an effective tool in simulating complex systems that have multiple forms of spatial diffusion.

KEY WORDS: spatial relationship; cellular automata; relational database; culture diffusion; spatio – temporal simulation

CLC number: P208

Document code: A

Article ID: 1002-0063(2002)04-0359-07

1 INTRODUCTION

The functionality of spatio-temporal analysis and modelling is a drive for GIS to further applications in various applied fields and digital earth plans. However, current commercial GIS lacks those capabilities for spatio-temporal distribution, prediction, and simulation of spatio-temporal processes, and especially do not have the ability to simulate complex dynamic interactions among economic, human, cultural and ecological processes (ZHANG and CUI, 2000). Thus, there is an urgent requirement for traditional GIS to provide not only spatio-temporal data management services but also tools for scenario generation. The basic thought to study

complex spatial system is to apply the theory of complex systems, combining the essential rules of geography, selecting proper study methods, and designing proper models. As a result, more effective and powerful methods for studying complex systems have begun to be applied in order to understand geographic systems; for example, system dynamics, neural networks, artificial intelligence, etc. (ZHOU *et al.*, 1999). The integration of GIS and dynamic models has become an important area of research on GIS because it greatly improves the ability of GIS to support spatial decision-making and simulate geographical processes. The fundamental problem, however, is that the conceptual representation of space and time in dynamic modelling and in GIS are not com-

Received date: 2002-09-16

Foundation item: Under the auspices of the National Natural Science Foundation of China (No. 40071071).

Biography: LUO Ping (1974 –), male, a native of Jinzhou City of Hubei Province, Ph. D. His research interests include spatial model and geography information system.

patible (TAKEYAMA and COUCLELIS, 1997) Cellular Automata (CA), with the ability to calculate time and space, are a potential solution to the incompatibility between GIS and dynamic models. Consequently it has been noticed by an increasing number of scholars and has become an active area of research on the field of complex systems science. Standard CA has well-developed methods for studying cells and lattices based on geometrical characteristic, but within standard CA it is impossible to simulate complex systems that have multiple, spatially diffused forms, such as the diffusion of cultural innovation, the spatial diffusion of business, and war invasion scenarios etc. The main reason why standard CA cannot simulate such systems that interact at a distance is that the spatial relation of an object is based on geometric characteristics in standard CA, but there are many spatial relationships based on non-geometric characteristics in the real world. The paper will expand the standard CA model, discuss the possibility and flow of RDB-based CA, construct a CA model based on relational databases that explains the diffusion of cultural innovations, and provide a case study on the diffusion of fashion wear trends to act as an example of this new model.

2 CELLULAR AUTOMATA AND ITS LIMITATIONS

Cellular automata models are discrete-time system models with spatial extensions. The ability of cellular automata to model the complex order hidden in spatial details has been demonstrated. The basic form of the model consists of cells, states, neighbourhoods and transition rules. The states of the cells undergo iterative changes according to transition rules. Transition rules are functions of the cell's state and the state of neighbouring cells. The spatial behaviour of the process and the spatial interactions among spatial processes can be expressed by transitional rules. CA's main advantages in geographical and environmental modelling lie in three aspects. Firstly, CA easily combine with the spatial information stored in GIS, moreover remote sensing data and data from other image sources can both serve as data sources in CA. Secondly, CA is capable of generating very complex, global spatial patterns by using simple, local transition rules. CA produce a fractal structure, which is a natural representation of a hierarchy between local and global behaviour (SHI and MATTHEW, 2000). Finally, CA has other characteristics including bottom-to-top spatio-temporal modelling, functions for highly complex calculations, and highly dynamic qualities, among others (BATTY and COUCLELIS, 1997).

However, standard CA has some restrictions in cellular shape, neighbourhood and neighbour rules, which restrict the CA's ability to model complex, real world situations. The main reason is that object's spatial relations are based on geometric characteristics in standard CA. For example, according to standard CA, the cell's neighbor in one dimension is often defined by the distance from the first cell, cells in two dimensions are often defined within regular spatial mappings such as a grid, and a cell's neighbors are defined in relation to that cell by rules laid down by VON Neumann, MOORE Margolus, and others. Cellular transition rules generally cannot be applied to more distant cells. But in the real world, geographical and environmental systems possess more complicated characteristics such as irregularity, mutual interaction, identical branching, and more spatial relations are represented through non-geometrical characteristics. For instance, it is uncertain that religion and culture diffuse along adjacent cultural areas, and art or fashion trends tend to diffuse between similar cities rather than adjacent cities. Therefore, studying a cell's spatial relations and expanding the definition of a cellular neighborhood is necessary.

3 A CELL'S SPATIAL RELATION AND ITS NEIGHBOR DESCRIPTORS

CA is capable of studying the complexity of global spatial patterns based on the spatial interactions of a local unit. In fact, local spatial relation is hidden in neighbour and transition rule and the CA model iterative results represent whole spatial relations. So, in some sense, spatial relations and spatial conceptions are CA's unique advantage as a dynamic model. Spatial relations can be established not only by a spatial object's geometric characteristics such as position, shape and measurement, but also by its non-geometric characteristics such as name, sort, degree etc., which result in a statistical correlation of spatial objects, spatial self-correlation, spatial interaction, spatial dependency, etc. (GUO, 2001). According to CA theory all neighbours of a cell should be the aggregation of some cells that are capable of affecting the cell's next state. Therefore, to simulate the complex, real world more effectively, a cell's spatial relation is needed to consider not only a spatial object's geometric characteristics but also its non-geometric characteristics. Furthermore, we can expand the definition of a cell's neighbour, and consider that a cell's neighbour lies not only in spatial adjacency but also in attribute correlation. To model CA easily this paper puts forward that a cell's spatial rela-

tion between two different cells can be divided into three types: spatial adjacency, neighbourhood and complicated separation. Spatial adjacency is defined that the distance between two different cells is 0 or less than a pre-specified numerical value. A spatial neighbourhood is defined that the distance between two different cells is bigger than 0 or larger than a pre-specified numerical value. All other spatial relations between two cells except spatial adjacency and spatial neighbourhood are defined as complicated separation relation. For example, as shown in Fig. 1, the relation between point object (I) and area object (II) is spatial neighbourhood, the relation between area object (II) and line object (III) is also spatial neighbourhood, the relation between point object (I) and line object (III) is complicated separation. In the real world it is not certain that neighbouring geographical objects interact, and it is not certain that the geographical objects that interact are adjacent to each other. Standard CA has come to the top in simulating spatio-temporal systems based on spatial adjacency relations. But, because its theory is based on geometric adjacency and it does not thoroughly analyse a cell's neighbourhood relation and complicated separation relations, the standard CA's ability to model complex, real world environments is restricted. So we must expand standard CA to solve two problems: 1) the description of a spatial neighbourhood relation; 2) the description on cell's complicated separation relation.

Spatial adjacency relation describes the distance and relative position relationships between cells. Because the study on topology relation of spatial database mainly including spatial adjacency relation has come to the top, the basic thought is transforming spatial neighbourhood to spatial adjacency by dividing space, and then constructing an information table that can be queried. Some scholars divide the spatial area of research objects by a Voronoi map, which is able to transform some geographically non-adjacent objects into spatially adjacent relations. A Voronoi map is an effective tool that constructs the relation because it has the ability of dividing spatial objects effectively. As shown in Fig. 1, the spatial adjacency between point object (I) and area object(II) has been transformed to spatial neighbourhood between area object(ABH) and area object (HBCFG), the relation between area object (II) and line object(III) has been transformed to spatial neighbourhood between area object (HBCFG) and area object(CDEF). Generally, a Voronoi map is transformed into a Delaunay triangle net in most research articles because the Voronoi map of line objects and area objects is quite complicated.

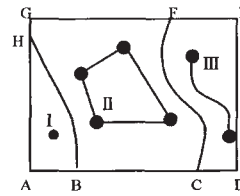


Fig. 1 Neighbour cells spatial relation transition from neighbourhood to adjacent

The description of complicated separated relationships is more complicated. As shown in Fig. 1, there are spatial interactions unable to be described by adjacency and neighbourhood relationship between point object (I) and area object (II) and line object (III). Firstly, the state of area object(II) does not affect the next state of point object (I), but the state of line object (III) affects the next state of point object (I). So point object(I) and line object(III) should become neighbours, but area object(II) and point object (I) shouldn't become neighbours. Secondly, both area object(II) and line object(III) affect the next state of point I, so both area object (II) and line object (III) should become point object(I)'s neighbours. It is impossible to solve some complicated non-adjacent spatial relations by the use of a Voronoi map. So we must design a new method. Extending CA based on RDB is an academic experiment, in which some fields are designed to describe the essential information needed to define and select a cell's neighbour.

4 CA'S CONCEPTUAL MODEL BASED ON RDB

4.1 Cellular Attributes Datasheet in CA's Model Based on RDB

Two principles should be considered in modelling CA. 1) The integration and compatibility principle: CA should have the ability to integrate with GIS and be compatible with spatial databases. 2) The reality principle: We should make cellular shape, neighbour rules and transition rules consistent with the real world. The basic idea of CA based on RDB is that of the cellular spatial relationship, where we consider not only an object's geometric characteristics but also its non-geometric characteristics, and defining and selecting a cell's neighbour based on a relational database, in which some fields are designed to describe the basic information needed to define a cell's neighbour. Some basic fields are necessary. As shown in Table 1, the first is the field "CellID" which is used to describe cellular coding. The second is the field "Position" which is used to describe

cellular position. The third is the field “CellularState” which is used to describe the cellular state’s value. The fourth is the field “NeighborInformation” which is used to describe the cellular neighbor qualifications, often including level, sort, characteristic, etc. The fifth is the field “BelongCell” which is used to describe those cells whose neighbor is the current cell. The sixth is the field “IncludeCell” which is used to describe those cells who are the current cell’s neighbors. The last is the field “NeighborNumber” which is used to describe the number of the cell’s neighbours.

Table 1 The cellular attribute datasheet in CA’s model based on RDB

Name	Description
CellID	Cellular coding
Position	Cellular position
CellularState	Numerical value of cellular state
NeighborInformation	Basic information relevant for defining a cell’s neighbours—or example, grade, sort, scale, etc.
Belong Cellular	Those cells whose neighbours include the current cell
Include Cellular	Those cells whose neighbours belong to the current cell
Cellular Number	Number of cellular neighbours

4. 2 Flow Chart of Extended CA Based on RDB

As shown in Fig. 2, the flow chart of an expanded CA based on RDB includes five steps. The first is initialization. An object’s area and cellular lattice is established and saved in GIS according to the purpose of the study. The object’s database structure is updated automatically, records are added in the cellular attribute table, and its attributes are inherited by the cell’s attributes. The second is defining a cell’s neighbour rules and preparing the cells for data. The rules to select a cell’s neighbour will be established according to whether the rules will affect or not a cell’s next state. Then data are confirmed according to the neighbour selection rules and taken from the GIS’s database, amended, and input as the field’s “NeighborInformation” value. It can then be applied to spatial analysis, to query neighbours, and be prepared to construct the cellular neighbour relationship. The third is querying a cell’s neighbour and establishing their spatial relationship. At first, data processing for the “NeighborInformation” item is performed on the basis of neighbour rules using means such as buffer analysis, spatial statistical analysis, clustering analysis, etc. Then a cell’s neighbours are identified, and the field “IncludeCellular” and the field “BelongCellular” are evaluated. Finally in this step, a cell’s spatial relationship is established. The fourth is calculating ac-

ording to transition rules. Transition rules are established, the numerical value of a cell’s next state is calculated according to the transition rules, and the field “CellularState” is evaluated. The fifth step is dynamically updating the transition rules. It is necessary because dynamic transition rules are more effective in the real world.

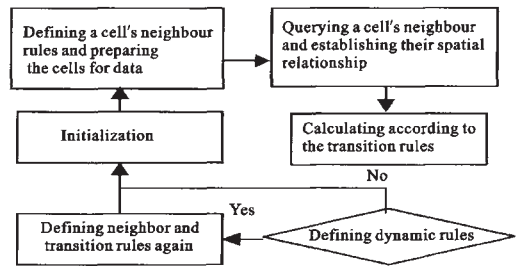


Fig. 2 Flow chart of an expanded CA based on RDB

5 CASE STUDIES ON SPATIO-TEMPORAL SIMULATION

The expanded CA based on RDB is an effective tool in simulating complex systems that have multiple forms of spatial diffusion. The diffusion of cultural innovations possesses many forms of spatial diffusion and therefore was selected as a study object.

5. 1 Influencing Factors and Diffusion Types on the Spatial Diffusion of Cultural Innovation

The essence of the diffusion of cultural innovation is the spreading and diffusion of cultural innovation information based on time and space, or is it’s physical diffusion in a spatio-temporal dimension, whose internal drive is the gravitation generated by the difference between area objects and the culture organism’s demand to survive (WANG and GENG, 1998). The influencing factors in the diffusion of cultural innovation mainly include cultural innovation’s potential energy “*v*”, spatial distance “*r*”, spatial diffusion friction “*mc*” and cultural inertia “*yc*”. The mathematical expression of cultural innovation diffusion’s influencing factors are thus defined as:

$$S = f(yc, r, v, mc) \tag{1}$$

where *S* is the culture innovation numerical value that a region has received from another region; *v* is the gravitation between different areas and is decided by the degree of discrepancy between different cultural areas having discrepancies in resources, environment, conventions history, etc.; *r* is spatial distance to which *S* is in inverse proportion because of friction and infor-

mation's loss in cultural diffusion; mc is the spatial friction including resistances generated by terrain, governments, military affairs, religion, etc. Spatial friction not only baffles but also distorts the diffusion of cultural information. The coefficient of spatial friction can be designed to measure the extent to which factors hinder diffusion, and its value can range from 0 to 1 (WANG and GENG, 1998). Where yc is cultural inertia, which means that traditional moral, religious and legal notions have a rootedness and tend to adhere to traditions.

Based on a review of current research we can divide cultural diffusion into five basic types according to geometric relationship, probability and selection. This paper posits that those five basic types are adjacency diffusion, adjacency probability diffusion, adjacency selection diffusion, non-adjacency selection diffusion and non-adjacency probability diffusion. Adjacency diffusion means that cultural innovation will diffuse when a spatial adjacency relationship exists without regard to grade or sort. Adjacency probability diffusion means that cultural innovations diffuse by probability despite an adjacency relationship. Adjacency selection diffusion means that cultural innovations diffuse selectively despite an adjacency relationship. Non-adjacency selection diffusion means that cultural innovations diffuse selectively despite a non-adjacency relationship. Non-adjacency probability diffusion means that cultural innovations diffuse by probability despite a non-adjacency relationship. In general, non-adjacency diffusion has the discrete and inlaid feature in spatial shape, and probability diffusion based on haphazard is irregular in spatial shape.

5.2 Modelling a Cultural Diffusion System Based on CA

Equation (1) describes the interaction between two objects. In fact one culture object area is often affected by numbers of culture object areas in the real world. So based on equation(1) the innovation diffusion's cumulative value that describes what one culture object area receives from other object areas can be calculated as:

$$G = \sum S_i = \sum f(yc, r_i, v_i, mc_i) \quad (2)$$

$(i = 1, 2, \dots, n)$

where G is the innovation diffusion's cumulative value, n is the number of neighbour cells, yc is relevant to the cell's historical state, r_i , v_i , and mc_i is relevant to other object areas' attribute values. So equation (2) can be transformed as:

$$S_i = f_1(S_{i-1}, \sum f_2(r_i, v_i, mc_i)) = f_3(S_{i-1}, O_1, O_2, \dots, O_i, \dots, O_n) \quad (3)$$

$(i = 1, 2, \dots, n)$

where S_i is the cell's current state, S_{i-1} is the cell's previous state, f_1 , f_2 and f_3 are functions, O_i is the state of the diffused source i that affects the current cell's state. Equation (3) is a normal descriptive form of the cell state's transition rules. Therefore the conceptual model described by equation (2) can also be described by the cellular automaton model as:

$$S_i = S_{i-1} + \sum H_i \quad (i = 1, 2, \dots, n) \quad (4)$$

where H_i is the instantaneous value that the neighbor cell i causes. It is difficult to model cultural diffusion based on CA because of the non-homogeneous character of its geographical space. For easy calculation, the diffusion from culture innovating source cell to culture accepting cell can be divided into two steps: 1) cultural innovation diffusion obeys the same diffused equation in every direction; 2) the culture accepting cell receives culture innovation through the function of spatial friction.

Suppose a culture cell's diffusion has probability, then large numbers of cell's diffusions is a probable process, and the process is a continuous Markov process that obeys the KerMoglov diffused equation. The innovation's diffused cumulative value accords with the Logical curve because Torsten Hagerstrand has proved that diffused velocity accords with normal school curve with temporal change. Therefore culture innovation's dynamic diffused equation based on non-homogeneous space is obtained as (HAN and BAO, 1996) :

$$C(r, z) = \begin{cases} C_{\max} \cdot \text{erfc}\{[r - \rho(z)]/[4\sigma(z)]^{1/2}\} & r \geq \rho(z) \\ C_{\max} \cdot \text{erfc}\{[\rho(z) - r]/[4\sigma(z)]^{1/2}\} & r < \rho(z) \end{cases} \quad (5)$$

$$D(r, z, \Delta t) = C(r, z) / [1 + a \cdot e^{-k \cdot \Delta t \cdot C(r, z)}] \quad (6)$$

$$\Delta t = t - t_0 \quad (7)$$

$$z = m_0 - m \quad (8)$$

where $C(r, z)$ is the saturated value of a cultural innovation that the culture accepting cell has received from the culture source cell, $D(r, z, \Delta t)$ is the instantaneous value of cultural innovation that culture accepting cell has received from the culture source cell in the time t , Δt is the time difference between t and t_0 , a and k are coefficients relevant to diffused time and diffused velocity, r is the distance between the culture source cell and the culture accepting cell, m is general culture level of the culture accepting cell, m_0 is general culture level of the culture source cell, C_{\max} is cultural innovation value of the source cell; $\text{erfc}(x)$ is the Gauss function; $\rho(z)$ is the coefficient function of diffused offset; $\sigma(z)$ is the diffused coefficient function. The mathematical expression between H and $D(r, z, \Delta t)$ is defined as:

$$H = mc \times D(r, z, \Delta t) \quad (9)$$

$$H_i = mc_i \times D(r_i, z_i, \Delta t) \quad (i = 1, 2, \dots, n) \quad (10)$$

where mc is from 0 to 1. When the culture source cell and accepting cell are similar in economy, society, culture, etc. and travel between the two cells is convenient, the numerical value of mc is 1. By contrast, when the discrepancy between source cell and accepting cell is very large and travel is impossible between the two cells, the numerical value of mc is 0. Therefore, to a random culture source cell and a random culture accepting cell, we would have the innovation diffused value H_i in condition that C_{max} , r , m , m_0 and mc are known and the function of $\rho(z)$ and $\delta(z)$ are established. Therefore the random culturally innovating cell's state value G can be calculated according to the neighbour cell's defined qualifications and the cellular state's transition rules.

5.3 A Case Study on the Diffusion of Trends in Fashion Wear

Fashion wear's diffusion is a typical process of the diffusion of cultural innovation. Its diffusion processes are affected by many factors including traffic, economy, governments, religion, climate, etc. This paper mainly discusses theory and methods and does not get involved in an actual geographical area because of the difficulty in collecting data.

Suppose that there is a study region whose basic condition is defined as follows. 1) There are a railroad and a river (or lake) in the study region which is divided into five sub-regions O, A, B, C and D. There is a city in every sub-region, and there is a fashion wear diffusing source in sub-region O. 2) There is a railway in sub region B, which provides convenient connection to sub-region O. The economy and culture are similar in sub-region B and O. 3) There is also a railway providing convenient connections between sub-regions O and D. Economic conditions are similar in sub-regions D and O, but there is large difference in culture and conventions between sub-region D and O because of the river. 4) There is no railway connecting sub-region O with A and the level of the economy and traffic is low in sub-region A. 5) Residents are culturally stubborn and proud in sub-region C.

A cellular lattice is divided into 100×75 cells. Neighbour relationships are defined as follows. 1) There are neighbour relationships between all the cells that belong to the city area. 2) In every sub-region, there are some developing cells that are similar to small towns in the real world. There are neighbour relationships between developing cells and city cells. 3) Ordinary cells select adjacent cells whose culture innova-

tion level is higher as a neighbour cell, and its diffusion obeys probabilities.

The cellular diffused rule is defined as follows. 1) The probability of adjacency diffusion and adjacency probability diffusion are both 50%. 2) The probability, direction and distance of non-adjacency diffusion are established according to travel and economic conditions in the attribute table. The innovation value of the culture source is defined as 100. According to general fashion wear's diffused rule diffused equation can be simulated by $C(r, z) = 100 \operatorname{erfc}[r(2.44 + 0.329z)]$. The value of spatial friction can be obtained by the economic field multiplied by the travel field in the attribute table. As shown in Fig.3 and 4, a simulation result that is capable of showing fashion wear's diffusion process is acquired after the fiftieth calculation through the CA program.

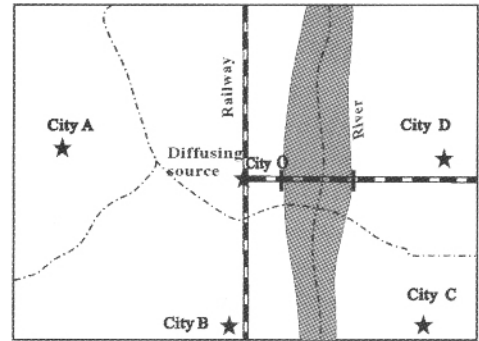


Fig. 3 Diagram of the experimental region's first state

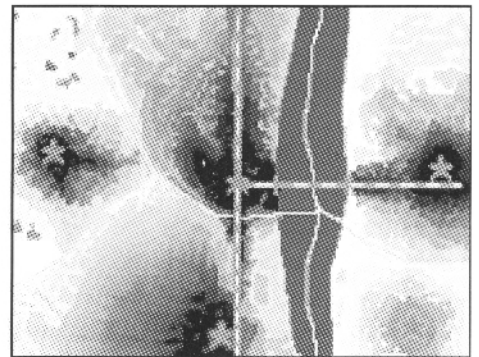


Fig. 4 Diagram of the cellular state after fifty calculations

Fig. 3 is the diagram of the experimental region's first state. Fig. 4 is the diagram of cellular state after fifty calculations. The basic character of fashion wear's diffusion is shown clearly by the experimental result as follows. 1) The diffused system has some characteristics of uncertainty. 2) Diffusion has the character of diffusing firstly between the same grade and attenuating

with distance. 3) Adjacency diffusion is the main diffusing form between each sub-regions. 4) Ease of travel and the river have a great selective role in the process of diffusion. 5) Mutual diffusion is not clear on the boundaries of sub-regions.

6 CONCLUSIONS

CA is simple in principle, wide in potential applications, hierarchical in nature, so they are powerful in theory. However the restrictions of standard CA limit their ability to model the complex real world. It is impossible to solve the CA's restrictions by expanding the CA model through traditional ideas. Current standards CA defining neighbour cell is mainly based on geometric characteristics, in fact there are a great deal of spatial relationships based on non-geometric characteristics in the real world (for example, business spatial diffusion, national economic aid crossing regions, the diffusion of popular culture, etc.) So a cell's spatial relation needs to consider not only a spatial object's geometric characteristics but also its non-geometrical characteristic. Furthermore, we can extend a cell's neighbour definition, and consider a cell's neighbour lies not only in the forms of spatial adjacency but also in attribute correlation. Extending a cell's neighbour definition based on RDB not only can simulate interaction among cells that are adjacent to each other but also can simulate interaction among cells that are non-adjacent. This not only provides a more natural manner to describe human knowledge but also provides a more effective tool to simulate complex, real world environments.

The culture innovation diffusion system has some rules and has a complex system's uncertain character. A case study on fashion wear's spatial diffusion process shows that cultural diffusion follows some rules and has some uncertain characteristic of a complex system, and culture innovation diffuse firstly between the same grade cell and attenuates according to distance. Ease of transportation, natural impediments such as rivers, terrain and conventions etc. have a great selective role in the process of diffusion. The result of the case study is consistent with academic forecast. Therefore studying

an expanded CA based on RDB not only has academic value but also has great potential in applications. CA has the advantage of simulating complex systems with multiple forms of spatial diffusion. Compared to the original CA, the RDB-based CA is a more natural and efficient representation of human knowledge over space. But expanded CA based on RDB still have some problems that need to be worked out. Among others, the tremendous data in cellular records remains a problem, as does a proper search for neighbours, and the proper transition rules. The analysis of these problems and further study will help GIS integrated with CA improve the level of decision-making support and the ability to simulate complex, real world environments.

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