Fuzzy cognitive maps-based modelling of residential mobility dynamics: GeoComputation approach

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Abstract

This paper is concerned with proposing a fuzzy cognitive maps (FCMs) driven approach for geocomputing urban dynamics (social, spatial and temporal) as a complex system. After an overview of FCMs, mathematical fundamentals methodology that this theory suggests are examined. Then, the formalization and algorithm implementation of a model apply to residential mobility in urban space based on FCMs is described. Very good results were obtained, demonstrating that the use of these modelling approach is good and reliable.

Keywords

Fuzzy cognitive maps, Cellular automata, Residential mobility, GeoComputation.

Introduction

Geographical systems are complex entities that require integrated spatial and temporal modelling approaches to better understand underlying patterns and processes. These modelling approaches are now multidisciplinary in nature as

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geographers are not the only ones examining the multifaceted issues embedded in spatial patterns and dynamics. Hence, it is challenging to clearly situate spatiotemporal modelling within the domains of geographic information science, geocomputation (Openshaw, 2014) or geosimulation (Bennson, Torrens, 2004). A useful way of placing spatiotemporal modelling concepts is to consider them as being located in the intersection spaces of these tree disciplines. So, the inspiration for further advancement in spatiotemporal can be found in domains such as artificial intelligence, computer science, and complexity science among others. In this regard, the wide recognition of FCMs as a promising modelling and simulation methodology for complex systems (Papageorgiou *et al.*, 2004), characterized by abstraction, flexibility and fuzzy reasoning promotes advanced research about large-scale geographical systems. Urban systems have been traditionally characterized by a large number of variables, nonlinearities and uncertainties. Modelling such systems can be hard in a computational sense and many quantitative techniques exist. Development of FCMs that accurately describe urban dynamics is a challenging task, which, in many cases cannot be fully completed based solely on human expertise. Interestingly, in the recent years we have witnessed the development of algorithms that support learning of FCMs from data (Xirogiannis and Glykas, 2004; Anninou and Groumpos, 2014).

Fuzzy cognitive map background

Fuzzy Cognitive Maps (FCMs), introduced by Kosko (1986), are powerful tools for modeling dynamic systems. FCMs describe expert knowledge of complex systems with high dimensions and a variety of factors. An increased interest

about the theory and application of FCMs in complex systems has been also noted, and their validity and usefulness has been proved in the various fields (Eden *et al.*, 2006; Eden *et al.*, 2007).

Theoretical foundations of Fuzzy Cognitive Map

Fuzzy Cognitive Maps (Kosko, 1988, 1993) are signed directed graphs: they consist of nodes, so-called "concepts" that are connected through arrows that show the direction of influence between concepts. Causal and cognitive maps have been used to describe decision-based systems (Axelrod, 1976). Fuzzy Cognitive Maps were supplied with fuzzy logic theory enhancing Cognitive Maps ability to present and model qualitatively dynamic systems. So, FCM is a soft computing modeling technique used for causal knowledge acquisition and supporting causal knowledge reasoning process. FCMs permit the necessary cycles for knowledge expression within their feedback framework of systems. FCMs originated as a combination of ideas and methods from fuzzy logic and neural networks theories and have been introduced by Kosko (1986). Neuro-fuzzy systems have been proposed as advanced techniques for modeling and controlling real world problems that are complex, usually imprecisely defined and require human intervention. Neuro-fuzzy systems have the ability to incorporate human knowledge and to adapt their knowledge base via optimization techniques. They can play an important role in the conception, description and modelling complex systems. FCMs are regarded as a simple form of recursive neural networks. Concepts are equivalent to neurons, but other than neurons, they are not either "on" (= 1) or "off"(= 0 or 1), but can take states in-between and are therefore "fuzzy". Fuzzy concepts are non-linear functions that transform the path-weighted activations directed towards them (their

"causes") into a value in [0,1] or [1;1]. When a neuron "fires" (i.e. when a concept changes its state), it affects all concepts that are causally dependent upon it. Depending on the direction and size of this effect, and on the threshold levels of the dependent concepts, the affected concepts may subsequently change their state as well, thus activating further concepts within the network. Because FCMs allow feedback loops, newly activated concepts can influence concepts that have already been activated before. As a result, the activation spreads in a non-linear fashion through the FCM net until the system reaches a stable limit cycle or fixed point. A FCM illustrates the whole system by a graph showing the effect and the cause along concepts. FCM is a simple way to describe the system's model and behaviour in a symbolic manner, exploiting the accumulated knowledge of the system. A FCM integrates the accumulated experience and knowledge on the operation of the system, as a result of the method by which it is constructed, i.e., using human experts that know the operation of system and its behaviour in different circumstances. Moreover, FCM utilizes learning techniques, which have implemented in Neural Network Theory, in order to train FCM and choose appropriate weights for its interconnections.

Fuzzy Cognitive Map representation

Figure 1 illustrates a simple FCM consisting of five (5) concepts and ten (10) weighed arcs. Thus FCMs are directed graph capable of modelling interrelationships or causalities existing among concepts. Concept variables and causal relations constitute the fundamental elements of an FCM. Concept variables are represented by nodes, such as C_1, C_2, C_3, C_4 and C_5. Causal variables always depict concept variables at the origin of arrows; effect variables, on other hand, represent concepts variables at the terminal point of

arrows. For example, looking in figure 1, at $C_1 \rightarrow C_2$, C_1 is said to impact C_2 because C_1 is the causal variable, whereas C_2 is the effect variable. Each concept is characterized by a number A_i that represents its value and it results from the transformation of the real value of the system's variable, for which this concept stands, in the interval [0,1]. Causality between concepts allows degrees of causality and not the usual binary logic, so the weights of the interconnections can range in the interval [-1, 1]. FCM models a system as an one-layer network where nodes can be assigned concept meanings and the interconnection weights represent causal relationships among concepts.

FCM is a graph shows the degree of causal relationship among concepts of the map knowledge expressions and the causal relationships are expressed by and fuzzy weights. Existing knowledge on the behaviour of the system is stored in the structure of nodes and interconnections of the map. Each one the key-factors of the system. Relationships between concepts have three possible types: (1) either express positive causality between two concepts: $w_{ij} > 0$ (2) negative causality: $w_{ij} < 0$ and (3) no relationship: $w_{ij} = 0$

The value of w_{ij} indicates how strongly concept C_i influence concept C_j. The sign of w_{ij} indicates whether the relationships between concept C_i and C_j is direct or inverse. The direction of causality indicates whether concept C_i causes concept C_j or vice versa. These parameters have to be considered when a value is assigned to weight w_{ij}.

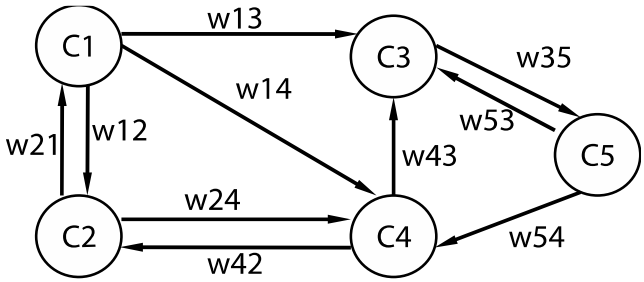

Figure 1 - A simple Fuzzy Cognitive Map model

Mathematical formalization of Fuzzy Cognitive Map

The simplest FCMs act as asymmetrical networks of threshold or continuous concepts and converge to an equilibrium point or limit cycles. At this level, they differ from Neural Networks in the way they are developed as they are based on extracting knowledge from experts. FCMs have nonlinear structure of their concepts and differ in their global feedback dynamics. The value A_i^{t+1} for each concept C_i at each time step is calculated by the following general rule:

$$A_i^{t+1} = f(k_1 \sum_{\substack{j=1 \\ j \neq i}}^{n} W_{ji} A_j^t + k_2 A_i^t) \qquad (1)$$

The k_1 expresses the influence of the interconnected concepts in the configuration of the new value of the concept A_i and k_2 represents the proportion of the contribution of the previous value of concept in the computation of the new value. This formulation assumes that a concept links to itself with a weight $w_{ii} = k_2$. Namely, A_i^t and A_i^{t+1} are respectively the values of concept C_i at times *t* respectively *t+1*. w_{ji} is The weight of the interconnection from concept C_j to concept C_i and *f* is a

threshold function. The unipolar sigmoid function is the most used threshold function, (Liu and Satur, 1999) where λ>0 determines the steepness of the continuous function f. The sigmoid function ensures that the calculated value of each concept will belong to the interval [0,1].

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \tag{2}$$

Materials and methods

The methodology approach followed for the implementation of the residential mobility FCM-based model consist of three discrete stages:

1- Concepts investigation for constructing the FCM. All the concepts that can affect the household's residential choice.
2- The causal relationships defined as fuzzy rules.
3- Cellular automata-based geosimulation

Concepts investigation for constructing the FCM

The Concepts used in the development of the model are derived from determinants of residential mobility. These determinants are directly related to the household's residential satisfaction that involves several influencing factors: objective residential environment, subjective residential environment, resident's characteristics and housing allocation institution.

Housing characteristics is the basic spatial scale of objective residential environment. Residents have high satisfaction with larger-sized and better forms housing. Chen, Zhang, and Yang (2013) analyzed Chinese residential survey data from Dalian and found that people are more satisfied with larger housing. Mohit, Ibrahim, and Rashid (2010)

investigate inhabitants of public housing in Kuala Lumpur, Malaysia and found that housing features, especially housing unit size, correlate positively with residential satisfaction. Ukoha and Beamish (1996) observed that residents in Abuja, Nigeria are dissatisfied with types of housing structure, building features and housing condition.

Neighborhood characteristics, such as neighbourhood quietness, greenness, cleanness and security, are the key factors influencing residential satisfaction. Most studies found that neighborhood security are dominant predictors of residential satisfaction (Cook, 1988; Salleh, 2008). Salleh (2008) investigated residents in Pulau Pinang and Terengganu state in Malaysia and found neighbourhood facilities and environment are the dominant factors affecting residential satisfaction. Parkes, Kearns, and Atkinson (2002) found that the neighborhood factors, especially the place and condition of neighborhood, are much more important in predicting residential dissatisfaction than are socio-demographic factors.

Public facilities or infrastructure such as transportation, schools, healthcare, shopping, banking and parking facilities determine the degree of life convenience and thus have influences on residential satisfaction. Lu (1999) found that residents in public housing in Hong Kong are dissatisfied with public transportation. Ha (2008) found that residents of public housing in Korea are satisfied with the availability of healthcare, shopping and banking facilities, but dissatisfied with parking and landscaping facilities. Mohit and Azim (2012) showed that residents of public housing in Hulhumale, Maldives, are more satisfied with their public facilities than with their housing condition.

The social environment, such as social relations and community cohesion and security, has influences on residential satisfaction. Adriaanse (2007) found that residential social climate, people's social perception of social

relationship, is the most significant factor to influence residential satisfaction. Mohit and Azim (2012) showed that inhabitants of public housing in Hulhumale are very satisfied with their social environment, especially regarding security and their relationships with their neighbors and community. Ibem and Aduwo (2013) found that people's cohesion and participation in the development of residences contributed to residential satisfaction.

Household characteristics such as age, sex, household size and income have been proved to have a direct impact on residential satisfaction. For example, age is identified as a significant determinant of residential satisfaction by many scholars (Ibem and Amole, 2012). However, the influence of some factors remains unclear because the existing empirical results conflict with each other. For example, although one empirical study found that household size is negatively correlated with higher residential satisfaction (Galster, 1987), others found household size is positively related to satisfaction (Cook, 1988). The inconsistencies might result from residents' housing preferences across various groups of people in different counties. Further, household characteristics determine someone's ability to realize their housing needs and goals (Schwanen and Mokhtarian, 2004). Income status is one of the main factors that indicate this ability.

It is believed that housing allocation institutions determining housing access type and housing adjustment freedom have an influence on residential satisfaction levels (Chen *et al.*, 2013). The level of freedom that one has to choose or adjust one's residential environment in order to get closer to one's residential preferences has an impact on one's resultant residential satisfaction. As home owning offers more freedom than renting, home owners are more satisfied than renters (Varady *et al.*, 2001). James (2008) found that subsidized renters in the US are more satisfied than non-

subsidized renters. In addition, as home ownership provides people with a sense of self-respect and pride, home owners are more satisfied with their residential situation than are renters. Empirically, Elsinga and Hoekstra (2005) showed that home owners are more satisfied than are tenants in many European countries.
Table 1 reports the concepts used to construct the FCM-based model of residential mobility.

Table 1 - Concepts investigated for constructing the FCM

Labels	Concept description
C_1	Income
C_2	Position in life cycle
C_3	Level of degree
C_4	Owner
C_5	Tenant
C_6	Other occupancy status
C_7	Single person
C_8	Childless couple
C_9	Couple with children
C_{10}	Single parent family
C_{11}	Land price
C_{12}	Rents
C_{13}	Amenities
C_{14}	Environmental quality
C_{15}	House
C_{16}	Apartment

The causal relationships defined as fuzzy rules

The above review of studies shows that while various factors could have influences on residential satisfaction, and the influences may vary in different groups, countries and

societies. For example, Parkes, Kearns, and Atkinson (2002) found the relative importance of neighborhood and socio-demographic factors is influenced by the characteristic of the place and time of their study. James (2008) emphasizes the influences of public housing project size on residential satisfaction.

This indicates that specific case study and empirical research of the determinants of residential satisfaction are needed to be carried out for better guiding public housing policies. In addition, the impact of housing allocation institution on residential satisfaction is little studied. In this paper, the expert's appreciation is taken into account. And the relationships between the determinants of residential mobility in term of concepts according to FCM-based modelling approach, are established using a series of fuzzy rules of the type "if the concept C_i is in s_p then the causal relationship with concept C_j is w_{ij}", where s_p is one of the possible states of the concept C_i and w_{ij} will be the value of the causal relationships for this state. In this way, a set of rules defining the value of the relationship is used to determine the relationship value between two concepts.

To define the set of rules, we define a general procedure. For instance, we assume that the state of each concept according to fuzzy sets in three zones illustrated in Fig.2.

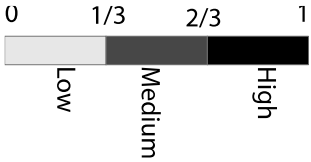

Figure 2 - Fuzzy state of each concept

The state can be defined as a fuzzy variable composed by three fuzzy sets: high, medium and low. Additionally, the possible types of relationships between concepts can be like linguistic variable (table 2). Also, the type of relationships

can be defined as a fuzzy variable composed by nine sets: Complete$^+$, High$^+$, etc.

Table 2 - Possible types of relationships between concepts

Value	Linguistic variable
1.00	Complete$^+$
0.75	High$^+$
0.50	Medium$^+$
0.25	Low$^+$
0.00	Null
-0.25	Low$^-$
-0.50	Medium$^-$
-0.75	High$^-$
-1.00	Complete$^-$

Then, we can define the following set of generic rules using the concept states and the possible types of relationships defined previously, to define the causal relationships between concepts:

- If the preceding concept is ***High*** and the consequent one is also ***High***, then the relationship is ***Complete$^+$*** (1.0).
- If the preceding concept is ***High*** and the consequent one is also ***Medium***, then the relationship is ***High$^+$*** (0.75).
- If the preceding concept is ***High*** and the consequent one is also ***Low***, then the relationship is ***Low$^+$*** (0.25).
- If the preceding concept is ***Medium*** and the consequent one is also ***High***, then the relationship is ***High$^+$*** (0.75).
- If the preceding concept is ***Medium*** and the consequent one is also ***Medium***, then the relationship is ***Medium$^-$*** (-0.25).

- If the preceding concept is ***Medium*** and the consequent one is also ***Low***, then the relationship is ***High***$^{-}$ (-0.75).
- If the preceding concept is ***Low*** and the consequent one is also ***High***, then the relationship is ***High***$^{-}$ (-0.75).
- If the preceding concept is ***Low*** and the consequent one is also ***Medium***, then the relationship is ***Medium***$^{-}$ (-0.50).
- If the preceding concept is ***Low*** and the consequent one is also ***Low***, then the relationship is ***Complete***$^{-}$ (-1.0).

The set of generic fuzzy rules follows an adaptation mechanism similar to the hebb learning rule (Papageorgiou *et al.*, 2003; 2004; Anninou and Groumpos, 2014). These rules would be used to determine all the relationships between the different concepts. Thus, every relationship would be determined under the same set of rules.

Cellular automata-based geosimulation

The cellular automata concept was introduced in the mid-1940s by John von Neumann (1951) and Stanislaw Ulam (1952) in the fields of mathematics, artificial intelligence and computing machinery (Turing, 1950). In the 1960s, John Conway presented "LIFE", a cellular automaton that is well known as "the game of life" and that is characterised by the following simple rules. A live cell stays alive if two or three of its neighbours are alive; otherwise, it dies. A dead cell will come to life if it has three living neighbours (Gardner, 1970). "LIFE" became the most famous basic rule in the "standard" CA and contributed greatly to its popularity.
Between the 1970s and the 1990s, conventional CA were proposed to model geographical phenomena such as spatial dynamics (Couclelis, 1985) and various spatial processes (Phipps, 1989; Ceccchini and Viola, 1992). Since Wolfram demonstrated the capability of CA techniques to generate surprising fractal patterns (Wolfram, 1984), conventional CA

have been used to study urban fractal forms (Batty, 1991). In spite of the value of conventional CA that mimic the complex nature of geographical systems, a conventional CA can be inappropriate when modelling and predicting complex and dynamic land use processes realistically (White and Engelen, 1994). For purposes of land use dynamics, a more complex CA model (e.g., Constrained CA model) is needed (White and Engelen., 1997). Simply defined, land-use is the human use of land cover (e.g., Corine Land Cover technical guide, EEA, 2000). The complexity of a land use system depends on: (1) the inherent qualities of land use, (2) the multiple local spatial interactions between land use types (Agbossou *et al.*, 2008; Agbossou 2010), (3) the neighbouring effects of land use activities, and (4) the aggregate level of demand for each land use activity. Naturally, time and various scale variables further complicate the linkage between the land-use system and the dynamics and therefore the rules and/or processes that permanently regulate the changes. Consequently, it is important to achieve several objectives in the modelling process: model and simulate related changes, dynamics and transformations, including their nature and content; the resulting processes, structures and configurations; and their location across time and space while predicting other potential changes. CA-based models can take these objectives into account (Portugali, 2004; Yeh and Li, 2002; Barredo *et al.*, 2003). This study, which mimics complex land use patterns, utilises the fundamental properties of CA based models, which include (1) a regular discrete lattice of cells. In this model, each land use type is represented by a particular cell state; (2) the evolution of each cell takes place in discrete time steps; (3) each cell is characterised by a state that is taken from a finite set of states; (4) the state of the cell at each iteration is determined by the states of the cells within a large neighbourhood and the transition rules based on the FCM dynamics derived

from fuzzy relationships rules (these transitions are identical for all cells in the lattice and represent the neighbourhood influences); and (5) the large neighbourhood effects influence the studied cells. These properties permit CA-based models to simulate the evolution of land use dynamics in response to the implementation of the residential mobility process.

Results and discussion

Experimentation of the model was carried out in the municipality of Saône (in eastern France). Each simulation is analyzed over a period of fifteen years with a reference situation, which is that of 2005. We postulate that, beyond 15 years, experimentation with our scenarios would be too prone to societal transformations to be valid. Thus, our simulations are performed over a period from 2006 to 2020. Also, for all scenarios the spatial resolution remained the same (we took a spatial resolution of 30 meters). The passage of the grid to the initial configuration (which is a model very close to the reality of the spatial distribution of different types of housing in the area in 2005). Five types of land use are identified: green space, building land, house rented, owner-occupied house and owner-occupied apartment is used in the simulations. Indeed, in the database used to perform this simulation are not involved in serviced apartments households, and therefore land use materializing this household category is not included in the simulations. However, we wish in future research include this land use through a weight made from the data. The results suggest that spatial planning policy to curb suburbanization could turn to a pre consisting in implementing the idea of the following scenario: a pleasant living environment for all and demographic balance. This would actually work in reducing

urban pollution of all kinds (noise, pollution, incivility, insecurity, etc.) and develop more amenities. It will also, of a socio-demographic point of view, introduce incentives to maintain strong family cohesion.
Indeed, analysis of the simulations of the spatial distribution of habitat for 2005-2015 shows that of temporality than 10 years, we do not observe an increase in the type of housing "apartment for rent".

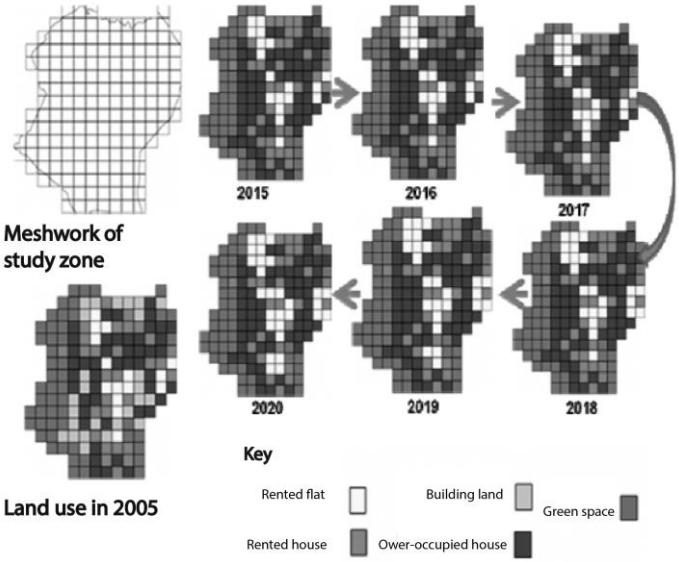

Figure 3 - From meshwork of study zone to results

Paradoxically, it is the habitat type "house property" that spreads. Faced with this result against-intuitive, we wanted to go further in the analysis. To do this, we launched the simulations of this scenario over a longer temporality, until 2020 (Fig. 3) by observing the type of household "Singles"

and "Single parent". Again, the results are surprising. The year 2015 was a pivotal year, a year that would mark a dynamic shift of residential mobility for this population of households with an increase in apartments and lower houses. Thus we see emerge the idea of conversion spaces materialize timidly across the housing types.
this result suggests us to focus in a forthcoming paper on the issue of the shrinking/reversing spaces in spatial planning.

Conclusion

This research introduces a new methodological framework for modelling, and simulating the residential mobility on the land use dynamics. The developed CA constrained by FCM-based model provides specific land use scenarios through 2020 that reflect the reality.
A comparison of the scenarios shows that each land use type obeys specific dynamics that are primarily the result of "push–pull effects" between different land use types, which are linked to the nature of the neighbourhood configuration and allow the model to run as a non-linear system. The allocation, distribution and redistribution of cells through space and time are central to the way that it allows the model to capture local spatial processes and to show net changes and growth in the study area.
The complexity of the land use systems and the long-term spatial effects of the residential mobility dynamics are significant. Therefore, the model was demonstrated to be appropriate. However, the model requirements pose several limitations that we have to investigate in futures work with appropriate a complex dataset that is geographically integrated and harmonised in time and in surveying methodology.

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