[AM-06-080] Capturing Spatiotemporal Dynamics in Computational Modeling

Abstract

We live in a dynamic world that includes various types of changes at different locations over time in natural environments as well as in human societies. Modern sensing technology, location-aware technology and mobile technology have made it feasible to collect spatiotemporal tracking data at a high spatial and temporal granularity and at affordable costs. Coupled with powerful information and communication technologies, we now have much better data and computing platforms to pursue computational modeling of spatiotemporal dynamics. Researchers have attempted to better understand various kinds of spatiotemporal dynamics in order to predict, or even control, future changes of certain phenomena. A simple approach to representing spatiotemporal dynamics is by adding time (t) to the spatial dimensions (x,y,z) of each feature. However, spatiotemporal dynamics in the real world are more complex than a simple representation of (x,y,z,t) that describes the location of a feature at a given time. This article presents selected concepts, computational modeling approaches, and sample applications that provide a foundation to computational modeling of spatiotemporal dynamics. We also indicate why the research of spatiotemporal dynamics is important to geographic information systems (GIS) and geographic information science (GIScience), especially from a temporal GIS perspective.

Keywords: computational model, human dynamics, spatial social network, spatiotemporal dynamics, temporal GIS, time, time geography

Author & citation

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Explanation

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1. Background

Our world is a dynamic one! Various phenomena evolve and change across space and over time. Spatiotemporal dynamics can take place at a fast or a slow pace, act in different forms (e.g., face-to-face interactions vs. online interactions), and exist in both natural environment and human society. With advances in computing technology, it is becoming

feasible to use computational models to represent, analyze, and visualize complex spatiotemporal dynamics. Spatiotemporal dynamics are closely related to the concepts of change and process, which involve what (object-based), where (location-based), when (time-based), and how (event/process-based). Conventional geographic information systems (GIS) take a snapshot approach that focuses on the locations of various objects (i.e., where and what) and uses static GIS map layers to implicitly deal with time (i.e., when). Although the snapshot approach enables researchers to examine the changes regarding what and where between the map layers of different time points, it has limitations in modeling events and processes (i.e., how) associated with spatiotemporal dynamics of both natural and human phenomena in the real world. For example, urbanization often involves various events and processes that lead to changes in urban boundary, land use pattern, economic system, among others. How to represent, model, and visualize events and processes in relation to objects, locations, and time in computational models to effectively and efficiently deal with spatiotemporal dynamics remains a challenging research topic in geographic information science (GIScience).

2. Basic Concepts of Spatiotemporal Dynamics

Spatiotemporal dynamics is a loaded term. Some important basic concepts are introduced in this section:

2.1 Space and Time

Conventional GIS represent various objects in the real world based on their (x,y) coordinates in an absolute space, which exists independently of objects and serves as a container of various objects. Two common GIS representations are object-based approach that fills a space with discrete objects and field-based approach that partitions a space into regular or irregular units to represent continuous distributions of phenomena. Câmara et al. (1996) design an object-oriented data model combining the ideas of fields and objects to analyze environmental progress. Some spatiotemporal analytics also use interacting objects or agents to explore how spatial patterns are formed and call for behavioral-driven models that are consistent with the fine-scale individual decisions (Ye and Mansury 2016). Besides the concept of absolute space employed in conventional GIS, relative space and relational space have become increasingly relevant to GIScience in today's world (Shaw and Sui 2018). For example, sensors on an autonomous vehicle constantly detect relative locations of surrounding objects. In this case, relative space is more relevant than absolute space in dealing with spatiotemporal dynamics. Relational space, which is based on topological relationships among various objects (e.g., social networks among Facebook users), also plays a critical role in spatiotemporal dynamics of today's world. Regarding time, it is mostly considered as linear time that moves in one direction. However, some phenomena have a cyclic pattern such as ocean tides and daily traffic patterns that require a reference framework of cyclic time. In the contexts of history and planning, we also need to work with branching time to represent different scenarios in the past or into the future. To record time in a database, Snodgrass and Ahn (1985) suggest a distinction between valid time (when an event occurs in the real world) and transaction time (when an event is recorded in a database). Representing these different concepts of space and time to deal with various types of spatiotemporal dynamics is an important research topic of designing a space-time GIS (Peuquet, 2002).

2.2 Identify, State, Change, Event, and Process

Merriam-Webster defines dynamics as “a pattern or process of change, growth, or activity.” Different objects often are distinguished from each other by assigning them a unique identity. Each object also possesses a specific state reflecting its characteristics (or attributes) at a given time. When an object transitions from one state to another state, a change occurs. Changes are triggered by events (e.g., a traffic accident) or driven by processes (e.g., urbanization). Events and processes can occur at various temporal scales. It sometimes is difficult to draw a clear boundary between events and processes because an event could be considered a process at a different temporal scale. In addition, objects could keep their identity after a change (e.g., Hurricane Andrew intensified from category 3 to category 4) or evolve into a new identity after a change (e.g., The Soviet Union was split into several independent states.) Conventional snapshot GIS can overlay map layers of different time points to examine changes. However, the snapshot map layer approach cannot properly represent and model events and processes behind the changes.

2.3 Time Geography

Torsten Hägerstrand developed the concepts of time geography to study individual human activities under constraints in a space-time context (Hägerstrand 1970). Time geography is best known for its notation system of space-time path, which represents the trajectory of an individual across space and over time, and space-time prism, which delimits the maximum space-time extent that an individual could reach under a given travel speed and a time budget. Time geography was not widely applied in empirical research in the past due to the costs of collecting individual tracking data and the limited computing power. With modern technologies that can track individuals almost anytime and anywhere and offer significantly higher computational power, time geography has received a revived attention (Shaw 2012). Hägerstrand (1982, p. 324) states that at the tip of each space-time path “stands a living body subject, endowed with memories, feelings, knowledge, imagination and goals.” He indicates that individuals pursue projects in various environments and at different scales to achieve their purposes and goals. He also uses the concept of diorama to indicate that each individual is situated in a context of other living and non-living entities that influence and are influenced by the individual (Hägerstrand 1982). Ellegård (2012, p. 18) points out that Hägerstrand “in his last major work and intellectual testament The Fabric of Existence (2009), he did not use the term time-geography even though the book as such is an exposé of his time-geographic concepts and its notation system – albeit with focus on the ecological world view.” This ecological world view provides time geography with an even broader theoretical framework to study spatiotemporal human dynamics within the context of external environment.

2.4 Spatial Econometrics

Paelinck and Klaassen (1979) initiated the investigation of spatial econometrics. Spatial econometric models deal with the spillover effects among geographical observations in terms of location, distance, and topology (Anselin 1988). With the increasing availability of space-time datasets, the analysis of cross-sectional spatial data has shifted to spatial panel data (Elhorst 2003). Spatial econometric models adopt panel data structures to measure spatial interactions across geographical observations in a dynamic context (Anselin et al. 2008). Spatial panel data allow for jointly controlling spatial and time-specific effects, in addition to more heterogeneity, less collinearity, and more degrees of freedom.

Furthermore, modelling large-size spatiotemporal socioeconomic data would enhance our understanding of individuals' spatiotemporal behaviors and their contexts, while the outcomes of such models could reveal socioeconomic trends from neighborhood to global scales (Arbia 2011; Ye 2017).

2.5 Temporal Geographic Information Systems

Conventional GIS take a snapshot approach and do not explicitly deal with time. Movements and dynamics are inferred by examining changes between different map layers in conventional GIS. Temporal GIS research started in the late 1980s (Langran and Chrisman 1988, Langran 1989). A number of temporal GIS models have been proposed since then, including time-stamped (e.g., Armstrong 1988), event-based (e.g., Peuquet & Duan 1995), movement-based (Laube 2014), activity-based (e.g., Chen et al. 2011), domain-based (Yuan 1999), and process-based (Brown et al. 2005). Goodchild et al. (2007) suggest a general theory based on a geo-atom model to integrate object-based and field-based modeling approaches. Geo-atom is the basic unit defined for a property Z by a point location x in four-dimensional space-time and the property value z(x) at the given four-dimensional point location, which is expressed as tuple(x, Z, z(x)). Geo-fields can be aggregated from geo-atoms for a specific property Z, and geo-objects can be aggregated from geo-atoms based on specific rules. Geo-dipoles are introduced to deal with interactions. Siabato et al. (2018) provide a comprehensive review of the modeling trends in temporal GIS over the past four decades. In general, the progress of temporal GIS covers the following phases: (1) manage locations only, (2) add time stamps as attributes for queries, (3) both location and time as part of objects that can support analysis and visualization of changes, and (4) modeling dynamic processes.

3. Specific Computational Modeling and Analytical Approaches for Spatiotemporal Dynamics

Various types of spatiotemporal dynamics require different computational modeling and analytical approaches to effectively and efficiently model their changes and processes. This section presents some common computational modeling and analytical approaches for capturing spatiotemporal dynamics.

3.1 Spatial Panel Regression

Spatial panel data refer to spatiotemporal observations either measured at points or aggregated over polygons (Elhorst, 2003). The interactions and associations between each observation pair is defined by a spatial weight matrix. Variations among and across observations over time are termed two sources of variation respectively. Such between and within variations are represented in the spatial panel regression models: the pooled ordinary least-squares model (running ordinary least-squares model on panel data), the fixed-effects model (the regression model's parameters or group means are fixed), and the random-effects model (implementing an individual specific intercept in the panel model). In the spatial panel model, both space-specific time-invariant variables and time specific spatial-invariant variables can be controlled to better test spatial interactions and spatial spillover effects (Elhorst, 2017).

3.2 Geographically Temporally Weighted Regression (GTWR)

As a temporal extension of the standard geographically weighted regression (GWR), GTWR is a local model which simultaneously considers spatial and temporal nonstationarity to generate local parameters for any sites in the study region (Huang et al. 2010; Fotheringham et al. 2015). Compared to GWR, GTWR incorporates the temporal dimension of spatiotemporal processes by embedding the time effect into the spatial regression parameters to quantify the spatiotemporal features of local nonstationary processes. Hence, GTWR can be adopted to assess variations of socioeconomic activities and environmental processes across space and time, such as urban sprawl and disease diffusion. Different from the GWR which only considers the spatial proximity between objects defined by spatial kernel functions, GTWR considers both the spatial and temporal effects. Thus, the estimation of GTWR model relies on an appropriate definition of local effects in both space and time as well as the specification of underlying weighting matrices for spatiotemporal relationships among the observations.

3.3 Exploratory Space-Time Data Analysis (ESTDA)

The purpose of exploratory data analysis can be summarized as detecting patterns, trends, and relations in data towards efficiently and innovatively formulating hypotheses. ESTDA has been developed to reveal the coupled space-time attributes of socioeconomic phenomena not identified otherwise (Andrienko and Andrienko 2006; Ye and Rey 2013). ESTDA highlights the following functions in a space–time context: interactively visualizing the dynamics of spatial distributions, revealing the spatiotemporal outliers, identifying the evolution of spatial association and clusters, and highlighting space–time statistical models. Through extending spatial (temporal) effect to exploratory temporal (spatial) data analysis, ESTDA can be systematically conducted by leveraging the ongoing efforts in spatial analysis and time series analysis.

3.4 Cellular Automata

Originating in evolutionary biology and artificial life, cellular automata (CA) is a discrete model composed of many simple and identical elements that interact locally with their immediate neighbors towards an emerging large-scale structure (Batty and Xie 1999). For instance, an urban cellular automaton is represented by a regular grid of cells with various states of land use, such as residential and commercial. Each cell’s value (land use) will evolve based on local rules. Such value is updated at each time step according to a mathematical function of neighboring units’ land use status at the previous time step. Hagerstrand’s (1967) spatial innovation diffusion model, Tobler’s (1979) cellular geography, and Batty and Xie’s (1999) urban growth simulation are among the classical applications of CA on modelling dynamics of geographical phenomena and spatial structures.

3.5 Agent-Based Models

An agent-based model (ABM) reproduces and predicts the simultaneous nonlinear operations and interactions of autonomous agents with social ability. Different from CA based on fixed spatial neighborhoods, agents in ABM can move across space to interact with each other and its neighborhood. As Jennings et al. (1998, p7) point out, “the agent-based view offers a powerful repertoire of tools, techniques, and metaphors that have the potential to considerably improve the way in which people conceptualize and implement many types of software”. Many ABM packages have been developed to carry out suites of simulations to explore the collective behaviors and emergent properties of complex

systems in a natural and flexible manner (Bonabeau 2002). ABM thus offer a bottom-up perspective to spatiotemporal behaviors and environment dynamics.

3.6 Trajectory Analysis

Trajectory analysis analyzes the objects that move or relocate over time. The behavior of an object can be revealed by analyzing the features of its trajectory such as pauses, velocity or direction of movement (Dodge 2016). There exist a wide range of trajectory tracking data such as mobile phone tracking data, taxi tracking data, online social network tracking data, shipment tracking data, and animal tracking data (Holloway and Miller 2018). Trajectory data track real-time movement paths sampled as a series of positions over time. Trajectory analysis also encounters the uncertainty issue in connecting sampling points, because low sampling rates are common. For instance, instead of linear movements, the Brownian bridge movement model assumes random movements (Venek et al. 2016). For analyzing high-speed movements in uncertain maps, the voxel-independence assumption needs to be relaxed (Heiden et a. 2017). In addition, rich and diverse information can be dynamically associated at each position, including human attributes, geographical features, urban structure, among others. Such information can be used to gain insights on the patterns and mechanisms of human movements (Shaw et al. 2016, Shaw and Sui 2018).

3.7 Spatial Social Network Analysis

One common approach of spatial social network analysis is to connect individuals in a social network to their associated locations in the physical space (Andris 2016). These spatial locations over time form individuals' activity space representing their social life. A space-time perspective can thus be embedded into social relationships, illustrating how geographic distance, proximity, and structure might shape social networks in the interrelated contexts over time. In addition, the behavioral dynamics of human in physical space is highly related to social relations in the virtual and relational spaces at different scales and levels, which has many implications on social-spatial interaction in urban planning and design (Ye and Liu 2018; Shaw and Sui 2018).

3.8 Spatiotemporal Visual Analytics

To develop innovative research questions from space-time data, researchers can benefit from iterative visual exploration and use their domain knowledge to guide the exploration process (Al-Dohuki et al. 2017). A spatiotemporal visual analytics software system should offer the following features: (1) powerful computing platform so that domain users are not limited by their computational resources and can complete their tasks over their own computers or mobile devices, (2) easy access gateway so that spatiotemporal data can be retrieved, analyzed and visualized by different domain researchers, and their results can be shared and leveraged by others, (3) scalable data storage and management which support a variety of data queries with immediate responses, (4) exploratory visualizations that are informative, intuitive, and facilitate efficient interactions, and (5) a multi-user system which allows simultaneous operations by many users from different places.

4. GIS and Spatiotemporal Dynamics Modeling

Many spatiotemporal dynamics modeling and analytical approaches discussed in the

previous section can be carried out without GIS. For example, Cressie and Winkle (2011) present various exploratory methods for spatiotemporal data, spatiotemporal statistical models, and dynamic spatiotemporal models from statistical perspectives. It also is feasible to perform agent-based simulation and network analysis to study spatiotemporal dynamics outside a GIS environment. Goodchild (2013) discusses the prospects for a space-time GIS (STGIS) based on seven distinct forms of space-time data (i.e., tracking, temporal sequences of snapshots, temporal sequences of polygon coverages, cellular automata, agent-based models, events and transactions, and multidimensional data). He concludes that, due to the great disparity in different types of space-time data and the scientific questions arise in each case, it is unlikely to see the emergence of a single space-time GIS and “a number of distinct forms of STGIS are likely to evolve, based on distinct data types and suites of scientific questions.” (Goodchild, 2013, p. 1076) There are two general approaches of coupling spatiotemporal dynamic models with GIS. Loose coupling is based on data exchanges between GIS software and external modeling software while there is no sharing of the database or modeling functions. Tight coupling, on the other hand, provides a development environment for users to implement spatiotemporal dynamic modeling functions within a GIS or implementing GIS functions within a modeling environment. These coupling approaches make it feasible to combine the power of GIS software with various spatiotemporal dynamic models that are increasingly available as open source software.

5. Spatial Spatiotemporal Dynamics Modeling Applications

5.1 Disease Spread

Because environmental and socio-economic determinants are correlated, spatiotemporal models can help us understand how disease cases cluster spatially and spread over time. Infectious disease can diffuse very fast based on transportation networks from local to global scales such as the influenza pandemics. Furthermore, urban hierarchy and distance decay are related to disease spread (Congdon 2016). To address spatial dispersal and time lags affecting the spread, many spatiotemporal models have been developed, such as space-time BME (Bayesian maximum entropy)-SIR (susceptible-infected-recovered) model on hand-foot-mouth disease and the traveling epidemic model of space–time disease spread in conditions of uncertainty (Angulo et al. 2013; Christakos et al. 2017). In addition, social media data can be used to track the emergence and spread of dengue fever based on spatiotemporal semantics of user posts (Ye et al. 2016).

5.2 Information/Meme Diffusion

The increasingly popular application of mobile smart devices has boosted the usage of various social media apps. Social media activities responding to different news have thus been integrated into daily activities of many individuals, forming social networks of message spread. Exploring the pattern and trend of meme diffusion across social networks can facilitate the preparation for natural disasters or human crises. For example, the open source package of SocialNetworkSimulator on github contains spatiotemporal models and algorithms to generate and analyze spatial social networks, detect user communities, and simulate information diffusion in the context of space, time, and network (Ye et al. 2018).

5.3 Urban Sprawl

Urban sprawl is featured by the discontinuous morphologies at the edge of cities. Batty (2013) suggests that cities can be better understood through living systems of networks and flows. Most urban sprawl models in practice utilize micro-level actions and across-scale interactions/flows to unravel the aggregate-level patterns, which can be used to guide land use regulations or transportation policies on growth. The relationship between land use and transport is usually explored. Geographical approaches taking the human motivations into consideration in spatiotemporal models can facilitate their applicability in the real world.

5.4 Human Activity Dynamics

Detailed data of individual activities and interactions are being collected by vendors, service providers, and government agencies. This information can reveal human mobility at fine spatial and temporal scales (Shaw et al., 2016; Shaw and Sui, 2018). The characteristics of individuals such as socioeconomic status and demographic features often affect their activity dynamics such as travel distance, frequency of visits to certain sites, and even the spatial structure of communities. Furthermore, the network among locations connected through human mobility can be used to identify functions of places and possible spatial mismatches between land use and individual needs (Liu et al., 2018).

5.5 Traffic Flows

Advanced technologies in sensing and computing have created urban trajectory datasets of humans and vehicles travelling on urban networks (e.g., roads and public transits). Analyzing and understanding the large-scale, complex data reflecting urban dynamics is of great importance to enhance both human lives and urban environments. For instance, TrajAnalytics is developed as cloud-based software of visualizing traffic flow data which can be accessed through Web browsers (Al-Dohuki et al., 2017). It supports users to load raw trajectory data and perform road-based and region-based map matching and aggregation to assess traffic flows.

5.6 Environmental Modeling

Environmental GIS modelling involves space-time statistical methods based on environmental monitoring data and other relevant context variables. For example, Yuan (1994) develops a wildfire GIS to support wildfire studies and operations based on four conceptual wildfire models: locational snapshots, fire entities, entity snapshots, and fire mosaics. Jagger et al. (2002) study seasonal hurricane activity by specifying local space–time coefficients of a right-truncated Poisson space–time autoregressive model. To enhance the conservation and management of wildlife, movement ecology research has been actively promoted to examine spatiotemporal mobility of animals, especially mobile species at risk (Fraser et al. 2018).

6. Summary

Geographic information systems have made good progress of representing and modeling where different features are located at a given time. When we move from a static representation to a dynamic representation of the world, it is far more complex than simply adding a time dimension to the spatial dimensions. Various processes that take place at different spatial and temporal scales interact with each other and lead to complex changes

to the phenomena being modeled. There exist many different approaches of conceptualizing spatiotemporal dynamics of phenomena in various application domains. Computational models for representation and analysis of dynamic phenomena under the concepts of absolute space, relative space, and relational space as well as with linear time, cyclic time, and branching time are likely to require different approaches and analysis functions to address their respective needs. This article presents some basic concepts and sample applications to illustrate how to capture spatiotemporal dynamics in computational modeling and its potentials to various application fields.

Moving from static snapshot GIS to temporal GIS that can better handle various types of spatiotemporal dynamics has attracted significant research efforts. There have been many data models proposed for temporal GIS and it remains a research challenge of developing a unified GIScience framework to integrate these different approaches and the definitions of space-time. It is also beneficial to compare the differences of spatiotemporal dynamics between different places. Spatiotemporal dynamics can be investigated at different scales (e.g., individual, local, meso, and global) and from multiple dimensions (e.g., spatial pattern, temporal trend, and statistical distribution) such that a comprehensive analytical framework can be systematically developed based on the combination of these dimensions and scales to identify research gaps and frontiers (Ye and Rey 2013). Open data movement and open source toolkit implementation with programming/scripting languages such as R and Python have promoted a dramatic paradigm shift in spatiotemporal dynamics research towards robust and reliable across-discipline collaboration.

Computing has been playing a central role in the development of new space-time models and applications, which shape our daily life from individuals to neighborhoods and up to global scales (Deng et al. 2018). However, the complexity underlying the space-time dynamics and the computing intensity associated with processing massive near real-time georeferenced databases pose constraints for scientific advancement in theories and methods. In addition, spatiotemporal autocorrelation and heterogeneity would bring further challenges to data summarization, optimization, and estimation (Anselin and Rey 2012). Modern accelerator technology and hybrid computer systems can be deployed to address the computation constraints in space-time statistics especially for the computing bottleneck in Monte Carlo simulation (Marjoram et al. 2003, Anselin and Rey 2012, Robert and Casella 2013. Though cyberinfrastructure provides a great potential of lowering the computing costs, most existing space-time data structures and analytical functions need to be re-designed to fit into high performance computing capacities. We are still at an early stage of overcoming the research challenges of capturing spatiotemporal dynamics in computational modeling.

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