AN EXPLORATORY STUDY OF COMPLEX SOCIAL SYSTEMS THROUGH SIMULATION

Ganesh D. Bhatt and Sandip C. Patel
Department of Information Science & Systems
Morgan State University
1700 E. Cold Spring Lane
Baltimore, MD 21251

E-Mail (G. Bhatt): ganesh.bhatt@morgan.edu
Telephone: (G. Bhatt): (443) 885-3640

E-Mail (S. Patel): sandip.patel@morgan.edu
Telephone: (S. Patel): (443) 885-3836

ABSTRACT

In recent years, researchers have shown a great deal of interest in studying complex systems. Even though the traditional techniques have provided powerful study-tools, a band of researchers have been dissatisfied with these techniques since such techniques provide only a macro-level understanding. Understanding complex systems requires a broader aspect of knowledge that can examine the micro-level activities to understand macro-level symptoms. For example, sociologists and economists have provided several reasons of social segregation among people of different races in city, but there has been little research on understanding how exactly social segregation, a complex system, takes place. In this paper, we model and simulate a characteristic of complex social system that shows how social segregations in a city take place as a result of small decisions.

Keywords: Complex systems, computer simulation

INTRODUCTION

In recent years, the study of complex systems has become an important area of inquiry among academic researchers and practitioners. Even though the area of complex systems in not new, a growing flurry of recent research in several fields at macro-level has led to renewed interests in understanding the behavior of complex systems. The theories of complex systems do not belong to a specific discipline, but rather used in almost every discipline, ranging from physics and chemistry to social sciences and organizations ((Macal & North, 2010; Merali & McKelvey, 2006). Chaos theory, networks theory, and agent-based theory are some of the examples of the field which study complex systems (Wiek, Ness, Schweizer-Ries, Brand, & Farioli, 2012).

The recent research interests in complex systems have been influenced with the use of the powerful and inexpensive computers, since simulations into computers can provide a better and clear perspective of complex systems.

Traditional Method of Scientific Inquiry

Traditional method of scientific inquiry is referred to as a reductionist approach. In reductionist approach, if a system is broken down successively, it can analyze the underlying behaviors of elementary particles such as molecules, atoms, genes, and other elementary particles. A reductionist approach considers that as we proceed upward from the elementary particles, we can infer the behavior of the assemblies of the object made of the elementary particles (Johnson, 2009). Although all the elementary particles follow the laws of physics and chemistry, physics and chemistry alone cannot throw light on the systems made of a large number of interacting parts. Admittedly, the reductionist approach has been quite fruitful because it provides specialization that allows researchers to delve deep into one specific problem and its solution.

Complex Systems

The underlying principle that governs complex system is that simple laws lead to complex systems behavior. For example, human brain is a collection of trillions of cells and about 100 billion of neurons. However, by looking at one neuron or even a collection of neurons would not tell much about human consciousness or human thinking (Coveney & Fowler, 2005). It is only when one looks at the firing of millions of neurons in the brain one can gain some insight about human thinking. In a way, complexity can be understood as a way of thinking about the behavior of interacting units, irrespective of whether atoms, ants in a colony, or neurons firing in a human brain. The rise of the electronic computer provided both the key and the catalyst to our exploration of complexity.

The behavior of complex systems cannot be analyzed by examining the behavior of a single part. To fully comprehend the behavior, a global or macro-level perspective is required. The mathematical tools used in complex systems are nonlinear dynamics, graph theory, agent based modeling, time series analysis, cellular automata, network theory, genetic algorithms and information theory depending on the problems. With the rise of powerful computers, simulation models based on computer algorithms have become popular. The simulation models show how the behaviors of a school of virtual fish --computer-generated replicas-- that have been trained to swim gracefully, hunt for food, and scatter at the approach of a leopard shark, or how the swarms of ants, based on pheromones, find the shortest routes for their foods.

Agent-Based Models

The theory behind agent-based models is that there are some phenomena that can provide better perspectives about the behavior of the complex systems by directly modeling them on the compute rather than analyzing through mathematical equations. The reason is that computer models provide an intuitive sense of how the models at the macro level behave (Ottino, 2003). The researcher can visualize how models behavior change under different conditions and how realistically they replicate the “real” phenomena. According to Ottino (2003:296), “The origins of agent-based modeling can be traced to cellular automata—rows in a check board that evolve into rows in a checkerboard that evolve into the next row based on simple rules. A physical example may be the propagation of fire in a forest. The trees may be represented as occupying a fraction of the squares in a checkerboard; the rule may be that fire propagates if two trees are adjacent via the face of a square. Thus, fire propagates though faces—up, left, and right, but not diagonally. More generally, the basic building blocks may be identical or may differ in important characteristics; moreover, these characteristics may change over time, as the agents adapt to their environment and learn from their experiences. . . .”

Various classes of cellular Automata (CA) have been widely studied to understand their emergent behavior from their local interactions. As CAs evolve through complex feedbacks processes, an analytical understanding of them is quite difficult. Therefore, computer simulations are often the primary means of gaining knowledge for understanding the behaviors of CAs. The striking visual configurations that emerge through local interactions provide examples of self-organizing. What is important in the above description is that von Neumann understood life in terms of the logic. For him it mattered little whether the life was based on physic-chemical systems or silicon chips or any other strata that can evolve and self-organize by itself. What is important is the emergent property that is evident on the macro level based on the interactions of micro-elements. Artificial life is thus a logical step in understanding the principles of natural life by simulating the fundamental dynamic properties of life. Artificial life, in a way, provides a good example of complex adaptive systems, since biological systems are the most complex systems that nature has provided. The artificial life replicates the principles of complex dynamic systems in physical stratum to better understand the some of the principles that govern real life.

At the most rudimentary level, a cellular automaton is represented either as a one-dimensional or a two-dimensional array of regular cells. At any given time, a particular cell is in a discrete state that is determined by the characteristics of its neighboring cells, based on some specific transition rules. The cells change their states iteratively and synchronously based on the recursive application of these rules. A CA is thus composed of four principle elements: a lattice structure, a state-space, neighborhoods, and transition rules. Lattice structure is theoretically an infinite plane consisting of a grid with squares. However, practically, CAs use finite lattice. The cell-space in CA is considered a closed environment, which is not influenced by external events except the explicit rules that govern the states of cells. However, recent years, research has made several adjustments in cell-states by opening the cell-space to outside influences. The neighborhood of a cell in the CA formalism consists of an individual cell itself as well as a set of adjacent cells. In strict two-dimensional CA this results in two possible neighborhood configurations: one is referred to as Moore neighborhood of the eight cells that form a square around the cell in question, and the von Neumann neighborhood of the four directly adjacent cells comprising a cross centered on a cell (Batty, 1997).

AGENT-BASED MODELING AND SOCIAL SEGREGATION

By looking at some of the key properties of complex systems such as interactions, nonlinearity, and complex feedback between the interacting parts, it becomes obvious that cities exhibit a complex phenomenon. The cities, like the stock market, not only enable tremendous amount of interactions among different agents---ranging from simple commuters to high-priced car passengers-but also lead quite undesirable macro-level results such as traffic congestion, road-rage, and accidents. According to Schelling, the large-scale spatial clustering of residence of different socioeconomic groups is a phenomenon that is the result of the complexity that takes place between the residents (Schelling, 1978). Similarly, Krugman (1996) argues that aggregate economies in cities operate from local-scale interactive dynamics. Also, according to Torrens (2000), cities exhibit fractal dimensionality, organization, and emergence. CA modeling has becoming an important perspective in understanding ranges of phenomena in cities—from traffic congestion, urbanization, socio-spatial dynamics and segregation, and economic movements (Portugali, 2000). CAs are thus becoming important tools for simulating different facades of cities (Portugali, 2008).

Thomas Schelling was the first to reason about the phenomenon of complex systems in social segregation (Schelling, 1978). Even though individuals of similar color might mildly prefer the company of each other, without realizing that its overall effect at the macro level. In a sense, each individual makes their own choices at the local level, but the overall effect of these choices at macro level can lead to social disaggregation. As Schelling argues that for example, blacks and whites may get along with one another, but a slight preference of whites to live near the whites and blacks near the blacks can over time lead to segregation. Initially, blacks and whites may be distributed randomly within the city. But some whites will move to the places where other whites are living, which is likely to increase the number of blacks in their own neighborhoods, resulting other whites to leave. Simulations can depict these phenomena how individual preferences can lead to different clusters of populations. For example, even a weak preference of living by of the same colors can lead to an overwhelming number of people around.

METHOD

To test how simple preferences of actors can lead to complex outcome, we simulated and executed test-runs. We created the simulator in Visual Basic.NET 2010. The program contains the GUI representing a grid of 21x21 checkboxes, with each checkbox representing a house (see Figure 1) with a total of 441 houses. The program provides features to randomly or specifically select houses as those occupied by a race (e.g., a native group).

The first step in running the simulator involves marking the houses that are occupied by a racial group. We refer to this racial group as the native group. The landscape of the houses marked by the initial occupancy is referred as the initial condition. To set the initial condition, our simulator allows specifying the exact percent of the houses occupied by the race randomly, or specifying the probability of each house to be occupied by the race. All the marked houses in each of the simulation run are shown as occupied by a family of the native group, while unmarked houses are occupied by a different race (i.e., white families). Then, we run the simulator with several cycles with one specific criterion.

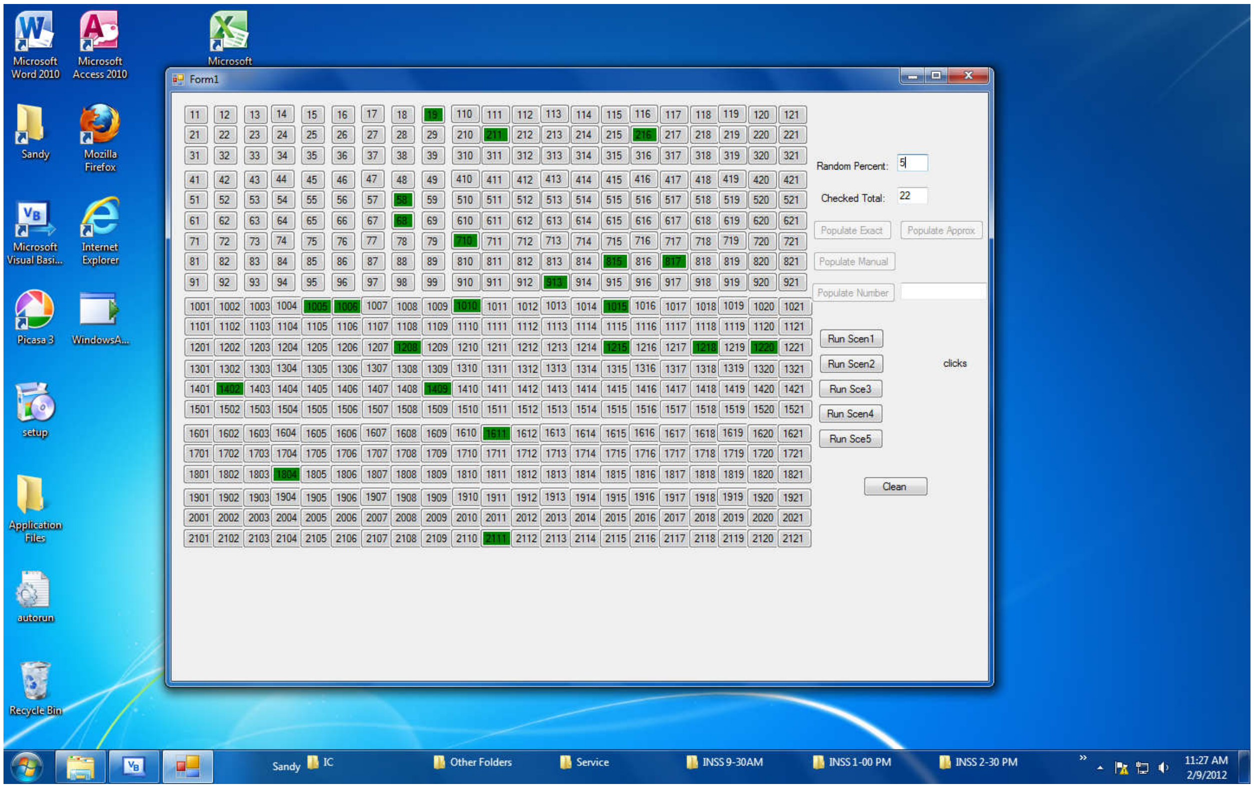

Figure 1: Initial Landscape: 5% Random-Occupancy by the Native Population (green cells show the native group)

Simulated Cycles

As explained above, the houses marked are defined as those occupied by the "native group" in a city population. Once the initial condition is generated, we run a desired number of cycles for showing the movement of families in and out of the city population. A cycle is meant to simulate a time period, such as a year. That is, a cycle represents the change in the neighborhood landscape of the city population within one time-unit. In other words, a cycle represents a next phase of occupancy by the native group in a given time period, such as a year. For this paper, we ran three cycles for different initial condition of the native group.

Simulated Criterion

In this study, we select a simple criterion of household movement from and to the city population. The criterion is that the native wants to live on the houses that are the nearest to other houses occupied by the natives. As the natives attempt to move into the houses that are adjacent to other natives, white race begins to move away from the city population. Each cycle of simulation shows how the household movement changes the landscape of the neighborhood in the city population with more natives moving in adjacent to the other native. For example, if the 3rd house in the second row of the neighborhood has a native group in the second cycle, the 2nd and the 4th houses in the third row become marked (i.e., occupied by the native group) in the third cycle. If there are more than one adjacent house occupied by the native group, then in the following cycle, each side of the consequent native houses is also marked as occupied by the natives. For example, if the 4^{th}, 5^{th}, and the 6^{th} houses in row five are occupied by natives, then in the next cycle, the 3^{rd} and the 7^{th} houses in row five also gets occupied by the natives.

The program depicts each cycle showing what the next new occupancy would look like between natives and whites, based on the above criterion. Each of the simulation test-run displays the racial landscape of the city population. Using the criterion listed above, we ran the simulator with 5%, 10%, 20%, and 25%initial condition in which natives randomly occupy the specified percent of the houses in the city population. In each of the test run, we see an emerging pattern that clearly shows the movement of whites away from the city population and movement of natives in the city population.

RESULTS

To test how simple preferences can lead to complex outcome, we ran different sets of simulations by setting the initial condition of the native group to 5%, 10%, 20%, and 25% randomly. Each of the simulation was run for three cycles, where each cycle successively changes the landscape of the native group.

To illustrate how local criterion of native group can lead to a complex structure of population based on the racial preferences, we begin with a random population of native group with 5%. That mean, the initial state starts with 5% of native group in the population of 441 houses. Therefore, we begin with random 5% (i.e., 22 houses) as the initial condition of the natives and rest 419 houses as occupied by whites in the population. In this landscape, we see that all the houses, except one block of 2 houses, adjoining to each other, are occupied by single native group (see Figure 1). After the first cycle of simulation, we find a large shift in the proportion of populations of natives in the city population. We find 15 different blocks of 3 houses adjoining to each other; 1 block with 4 houses adjoining to each other; 1 block of 5 houses adjoining to each other, and 1 block of 8 houses adjoining to each other have been occupied by native group. After running the second simulated cycle, we find a big shift in the population of the natives that varies from 1 block of 4 houses, 10 different blocks of 5 houses, 1 block of 7 houses, 1 block of 9 houses, 1 block of 10 houses, and 1 block 15 houses adjacent to each other are occupied by natives. In the 3rd cycle, the shift has been dramatic where we find several houses consisting of 8 blocks with 7 houses adjoining to each other; 1 block of 9 houses adjoining to each other; 2 blocks of 12 houses adjoining to each other, and 2 blocks of 17 houses adjoining to each other are populated by the native group (see Figure 2). Figure 2demonstrates how the population of native group has aggregated close to each other in repeated runs of the simulation cycles as well as how whites have successively moved away from the neighborhood.

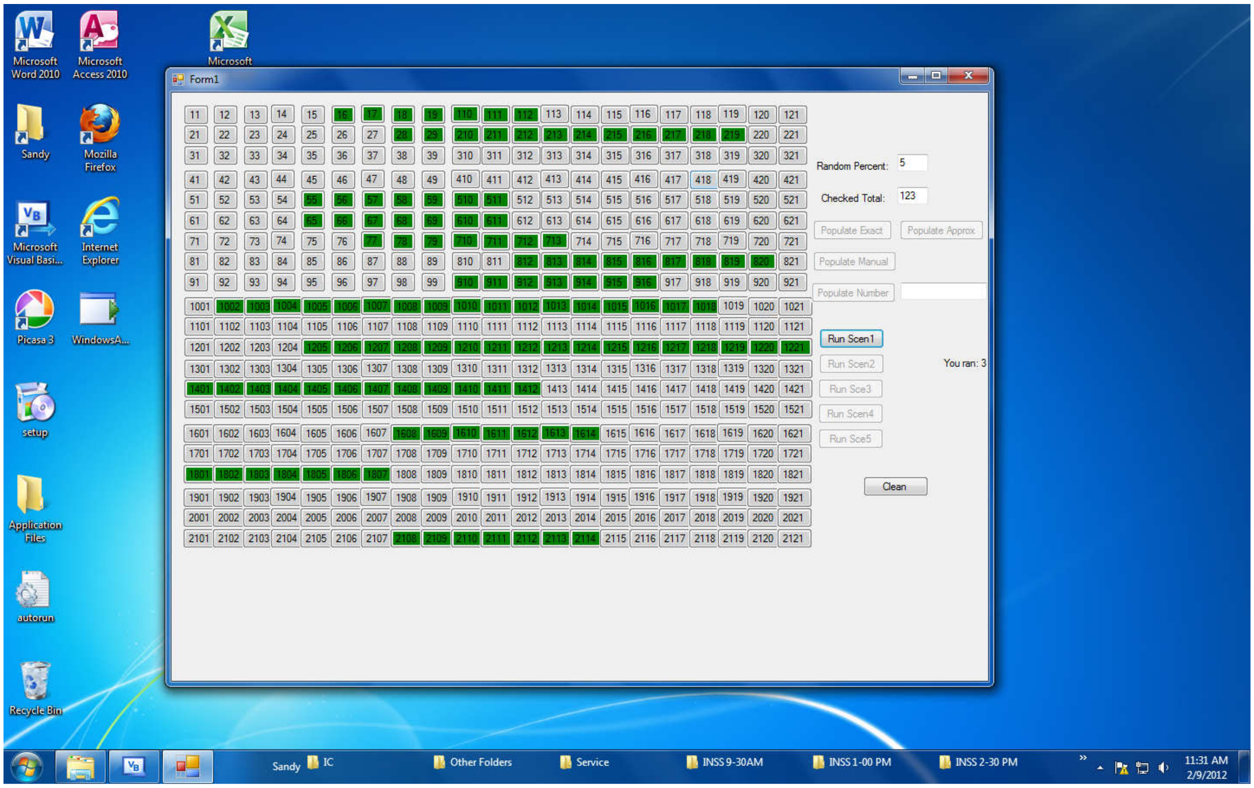

Figure 2: Landscape After the Third Cycle of 5% Initial Occupancy by the Native Population (green cells show the native group)

In the other detailed example, we examine the initial condition representing 1/5th of the city population consisting of natives. We begin with random 20% (i.e., 88 houses) as the initial condition of the natives in the city. Initially, we find that 65 single houses of natives are adjoining to the white's houses; 7 different blocks of houses with 2 houses in each block adjoining to each other occupied by natives; 3 blocks with 3 adjoining houses in each block were occupied by natives. After the first cycle of simulation, we find a large shift in the proportion of populations of natives in the city population ranging from 4 blocks with 2 houses adjoining to each other. We find 24 blocks of 3 houses adjoining to each other; 2 blocks with 4 houses adjoining to each other; 7 blocks of5 houses adjoining to each other; 4 blocks of 7 houses adjoining to each other; 2 blocks of 8 houses adjoining to each other, and 1 block of 11 houses adjoining to each other; and 1 block of 12 houses adjoining to each other have been occupied by native group. After the second run of the simulation, we find a huge shift in the population of the natives that varies from 4 blocks of 3 houses. There are 2 blocks of 10 houses, a block of 16 houses, a block of 17 houses, a block of 18 houses, a block of 19 houses, and a block of 21 houses adjacent to each other. After the 3rd cycle, the shift is dramatic where we find several houses consisting of 2 blocks with 11, 12, 16, 18 houses adjoining to each other; 3 blocks of houses are entirely (i.e., 21 houses) populated by the natives and one block consisting of 20 native houses.

DISCUSSION AND CONCLUSIONS

In this paper, we have studied how local-scale interactions in a city produce a complex macro-level pattern, such as social segregation. Even though our criterion to map the complexity of the city life is simple, our models can still show how individual interactions can lead to social complexity. To get a good grasp of these social phenomena, it is important to analyze basic movements of residents, which we have illustrated in this study. Coming to the grips with complexity, we need to look for other disciplines that have explored as many cases as possible through simulations. For example, research on ant colonies has been exploited in several disciplines. It is established that ants can find the shortest route to their food sources route by using the pheromones they release while moving. They can find the short trail even though each of the ants does not possess any skill or any visual cue to follow each other for finding the shortest route. The level of pheromones increases faster on the trails where ants find food quicker than the other trails since ants can make more the shorter trips than the longer one in a given time, which helps increase the level of pheromones. This increasing level of pheromones along the shortest route begins to attract other ants of their colonies to follow the same route. This property of finding the shortest route cannot be based on one individual ant; it is rather an emergent property of the collection and interaction of ants that lead them to follow the shortest route for the food sources. Several simulation-models of ant colonies have been devised to explore practical problems such as the traveling salesperson's problem, which deals with finding the shortest paths to travel all the cities that he/she needs to visit. In sum, our results show how unanticipated changes can occur from simple decisions that are made at the local levels. The results also show why global solutions cannot be predicted based on the optimizations of the local decisions.

References available upon request from the authors**.**