Visualization of Mobility-Density Relation in a Modified Percolation Agent-Based Model

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***Abstract*-- A modified percolation theory model was developed to incorporate agent mobility on the grid. In this agent-based model (ABM), the impact of agent density was found to significantly influence agent mobility. The visual representation software tool developed provides an intuitive understanding of the ABM simulation dynamics and mechanisms. The software tool visually illustrates that there is a relationship between mobility and density that would have to be taken into account for research into connectedness or connectivity (i.e., epizootic modeling) involving percolation models. Visualization is a common method that is often employed in many percolation models and studies as it helps in narrowing down regions of interest that can be followed up on in a more systematic manner.**

***Index Terms*-- Visualization; percolation theory; epizootic; agent-based model (ABM)**

I. INTRODUCTION

Percolation theory is not a new modeling method as a variety of models have already been created [1]. However, percolation models typically do not include mobility, and so that is the novelty introduced and explored here. The purpose of this research is to qualitatively examine the extent to which increasing agent population density limited mobility and to illustrate this through visualization software.

A percolation model involves a simple grid of interconnected nodes. Each node has adjacent nodes that they can affect and in turn are indirectly able to affect their adjacent nodes. Phenomena such as connectedness or connectivity related properties can be studied as second order phase transitions. In this way a phenomena can expand on the grid or eventually sputter out and stop. These transitions are associated with critical parameters such as the percolation threshold. The percolation threshold for an infinite grid would be the threshold for the occurrence of long range behaviour or long range patterns to emerge. The most common phenomena studied with percolation models are the formation of the largest cluster of connected components.

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A common use of a percolation model is the modeling of forest fires. In this model the percolation threshold would translate to the tree density above which the entire forest will be consumed by fire [2]. In mathematical terms, the percolation threshold is the critical value of occupation probability so that boundless connectivity occurs.

The two main types of percolation are bond percolation and site percolation. As shown in Fig. 1, site percolation considers lattice vertices as the relevant entities and bond percolation considers the edges as the relevant entities. This paper will use site percolation with each site representing an agent in an agent-based model (ABM).

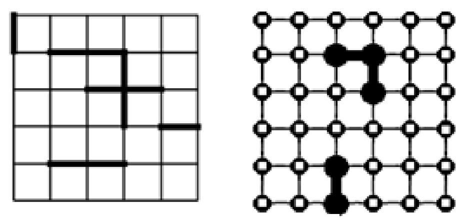

Fig. 1. Bond percolation (L); site percolation (R) [1].

Oleinikova used percolation theory to apply second order phase transitions to the process of cooling a liquid to the point where it froze; aggregating previously isolated microcrystalline structures into a larger frozen solid [3]. Recently, percolation theory is becoming more applied to epizootic research including work on plague bacteria passed by gerbils and the impact on the percolation threshold from gerbil tunnel connectivity [4].

II. ABM DESIGN AND VISUALIZATION

ABM is an area of increasing interest for modeling and simulation of human and animal phenomena, including disease spread. However, it is necessary to select the correct algorithm or model depending on the application. Some algorithms sacrifice precision for performance with techniques as simple as updating only a certain number of agents per simulation time step [5]. This increases performance but decreases precision, thus diminishing output data quality. Choosing an algorithm to use in an ABM simulation therefore depends on the aim of the simulation. For instance, particle simulations bear performance problems and a lack of system size scaling due to particle interaction with every other particle inducing an O(N2) complexity. Even for a minimal interaction such as a nearest neighbour interaction, it is still necessary to perform Euclidean distance calculations for every combination of two particles [5]. Our modified percolation model presents a novel method that may be suited to problems in particle simulation and ABM design.

Visualization methods may increase intuitive understanding of complex phenomena. For example, most timeline drawing or planning software uses temporal logic in order to visualize cases and Seker [6] introduces a visualization tool to illustrate his novel framework for relational event representation. Vespa [7] shows that Apollonian Packings and Networks are useful structures that may be used to solve many problems and having a tool to visually explore these structures is imperative for furthering research in this area. Likewise, our [8] visual software allows exploration of epizootics in a novel way and similarly [9] has a graphical user interface to allow interaction with a visualization tool.

III. MODIFYING PERCOLATION MODEL TO INCORPORATE MOBILITY

The model consists of a regular grid of 400-by-400 nodes, thus there are 160,000 points on the grid. Since each point represents a space or point that an agent may occupy, the maximum population would be 160,000 agents. However, having an overpopulated grid would not be a very interesting model. This is because any given agent on the grid can only move to a point if that point is unoccupied by another agent. Thus, the population used in this simulation is limited to allow for the observation of critical phenomena during the simulation.

Mobility is the associated with probability that an agent will move to a different location on the next simulation step or iteration step. For each iteration or loop through the program, a random number will be generated for each agent. The speed multiplier, as named on the program graphical user interface in previous work [8], is the mobility. Mobility can be set from “one” through “five”. A setting of “one” means that there is a twenty percent chance that the agent will attempt to move one grid unit in an arbitrary direction (20% x, 20% y) on the next program iteration, and “five” means that there is a one-hundred percent chance that an agent will attempt to move a grid unit in an arbitrary direction (100% x, 100% y) on the next program iteration. Zero mobility was not considered in detail here as it corresponds to the well-studied case associated with traditional percolation models.

The agent will not move to a given point if another agent already occupies that point. Thus, agent population density factors in adversely affecting the mobility. In terms of neighbourhoods, the mobility of the agent is restricted to a stochastic Moore neighbourhood, while its ability to spread a more conventional Moore neighbourhood [1].

TABLE I

PROBABILITY AN AGENT RELOCATES ON THE NEXT ITERATION.

Mobility	Movement in x or y	Agent movement
1	20 %	36 %
2	40 %	64 %
3	60 %	84 %
4	80 %	96 %
5	100 %	100 %

Table 1 illustrates the probability that an agent will move on the next iteration [8]. For the mobility setting of “one” (mobility = 1), there is a probability (p) of 0.2 that the agent will move along the x-axis. It will move either negative one (p=0.1) or positive one (p=0.1) along the x-axis. There is also an equivalent calculation for the y-axis. Thus, there is also a probability (p) of 0.2 that the agent will move along the y-axis; either negative one (p=0.1) or positive one (p=0.1) along the y-axis. This means that there is a 0.04 probability that the agent will simultaneously move along the x-axis and y-axis and this corresponds to a diagonal movement. As can be seen in Fig. 2, the 0.04 probability of moving diagonally is split equally by the four corners. Furthermore, there is a 64% chance the agent will remain in the same place.

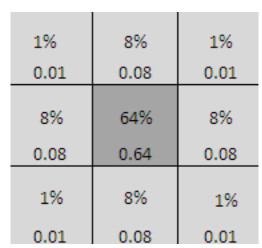

Fig. 2. Mobility set to “one”.

This agent mobility analysis can be applied to the other mobility settings. Figure 3 shows the probabilities for the mobility setting of “three”. Mobility incorporated into the traditional percolation model suits many ABM applications.

Fig. 3. Mobility set to “three”.

IV. EXPERIMENTS WITH A SINGLE AGENT

The simulation with a single agent (population set to one agent) verifies that with a higher mobility the agent is able to visit more unique points on the grid in a given number of iteration steps. As a corner case, this provides some basic validation of software tool mobility feature and the result is graphed in Fig. 4.

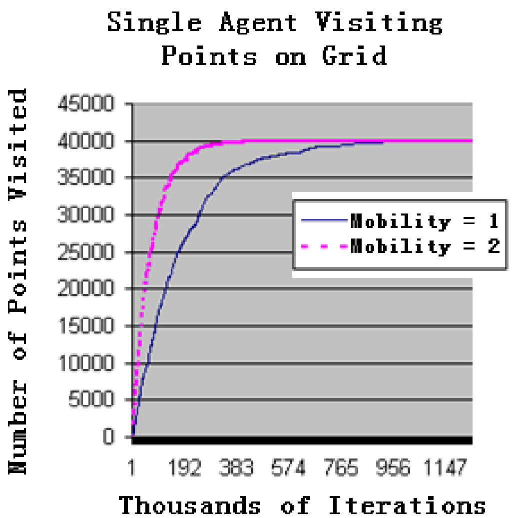

Fig. 4. With higher mobility the agent traverses more points.

Simulations were also performed to examine the path of a single agent and the area that it covered on a 200-by-200 grid. Figure 5 follows the path of an agent roaming in a free range that would represent a single agent in a given predefined space. Percolation models typically do not include mobility, which is the novelty investigated here.

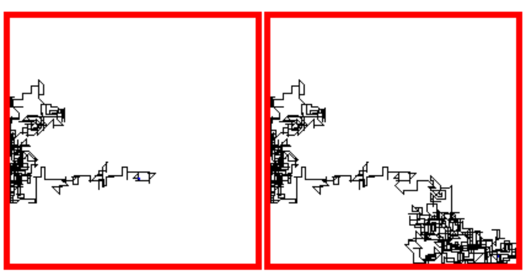

Fig. 5. Agent traversed 1389 points after 7214 iterations (left) and 3123 points after 15115 iterations (right).

V. VARIATION OF AGENT DENSITY

Simulations were done for varying agent population densities. The purpose was to qualitatively examine the extent to which increasing agent population density limited mobility. With increasing density, agent mobility is decreased since the area roamed after 3000 simulation iterations decreases. This validates our conjecture that population density adversely influences agent mobility and is plotted in Fig. 6.

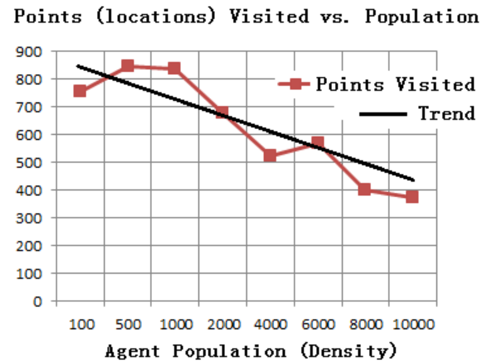

Fig. 6. Increasing agent density decreases agent mobility.

At all degrees of agent density (low, intermediate, and high), the trend is upheld that increasing density will decrease agent mobility. Figures 7 through 9 are snapshots from the simulation tool that depicts this finding. In Fig. 7, 846 locations on the grid were visited at a 500 agent population, and 835 locations on the grid were visited at a 1000 agent population. In a 200-by-200 grid, an agent population of 1000 or less is considered sparse.

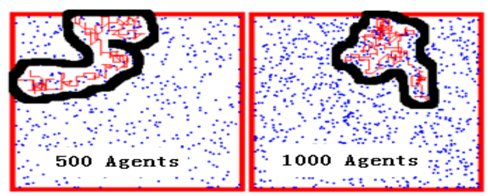

Fig. 7. Low agent density.

In Fig. 8 for intermediate densities, 675 locations on the grid were visited with an agent population density of 2000. With a density of 6000 agents on the grid, only 567 locations were visited. This may suggest that sensitivity analysis is needed for ABM output data when variables are interdependent.

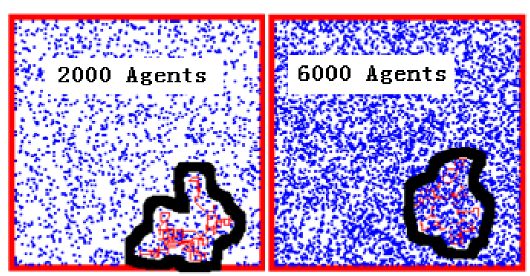

Fig. 8. Intermediate agent density.

In Fig. 9 at high agent population densities, 398 locations are visited by the agent at 8000 agent density and only 374 locations are visited at 10000 agent density. These results are all for 3000 iteration steps.

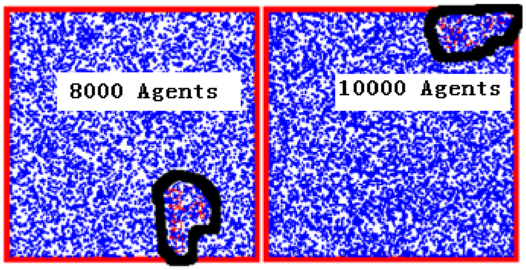

Fig. 9. High agent density.

VI. LIMITATIONS

There are some limitations associated with simplified scenario, if considering a deployment to a scaled-up ABM for epizootic research. In [8] it was suggested that the period of an agent being in a contagious state should be governed by a distribution as opposed to a specific duration. This also applies to the mobility and the neighbourhoods investigated in this study. It would also be interesting to track the movement of an agent within a facility using video or technologies related to Real-Time Location Systems perhaps using Wi-Fi tracking or ultra wide band tracking [9] to refine the mobility model. However, despite these limitations, a visualization tool has been developed to aid in understanding of a complex phenomenon. In our previous work [8] on epizootic spread, illustrated in Fig. 10, visualization software provides an intuitive feel of the problem.

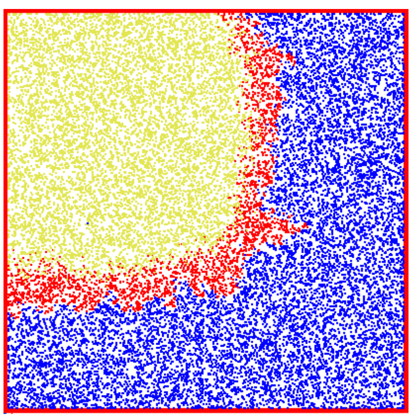
Fig. 10. Visualization tool [8] of ABM: red agents (mobile) are infected (contagious for set number of iterations); blue agents (mobile) not yet infected; yellow agents (immobile) died after infection (previously red).

VII. CONCLUSIONS AND FUTURE WORK

Our work shows a visual representation of agent mobility being impacted by increasing agent density in a modified percolation model. This ABM is a novel approach to disease spread research, both epidemic and epizootic, and may be well-suited for other research areas. For future work, several grid areas could be incorporated and linked through real-life links that exist in intensive unit production. This would require additional programming to model the various intensive unit production connectivity schemes that affect the spread of the disease on a larger scale, and to add other elements of fidelity and realism to an ABM built on percolation theory.

Mobility is the probability that an agent will move on the underlying grid and for each loop through the program, a random number will be generated to govern the probability. Based on this random number, and the setting of the “speed multiplier”, an agent will move one grid unit in a somewhat arbitrary direction on the next program cycle. Future work should examine the case where an agent can move more than one grid unit distance to simulate an increase in mobility before again mixing with the population. Also, a grid is not very representative of a continuum. In a more realistic model the agent should be free to move with unlimited degrees of freedom in a local area as the agent’s sphere of influence is that which predicates infecting a neighbour. Percolation models on a continuum exist and it would be worthwhile to investigate this further if the basic conjecture of using an ABM for an epizootic could be further substantiated.

It should be noted that there is currently limited ABM research on epizootic phenomena. As such this work illustrates that some of these modeling ideas initially intended to understand completely unrelated phenomena may have place in epizootic research.

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