Available online at www.sciencedirect.com

SciVerse ScienceDirect

Procedia Computer Science 10 (2012) 22 – 29

Procedia
Computer Science

The 3rd International Conference on Ambient Systems, Networks and Technologies (ANT)

Mobility and information flow: percolation in a multi-agent model

Martine Collard[a], Philippe Collard[b], Erick Stattner[a]

[a] *University of French West Indies and Guiana - LAMIA Laboratory*
[b] *University of Nice-Sophia Antipolis - I3S Laboratory (CNRS - UNS)*
Institut des Sciences Complexes - Paris-Ile-de-France (ISC-PIF)

Abstract

In real world situations, each person is generally in contact with only a small fraction of the entire population and exchange information through these interactions. Their number and their frequency vary from one to another individual and may be much depending on *mobility* of individuals. The objective of this article is to better understand how human mobility may have an impact on mobile social networking systems. This should help to answer a question as: "How might an information, a rumor, a pathogen, etc., driven by physical proximity, spread through a population?". We present a first stage of our work in which we focus on percolation processes as information flow mechanisms. We propose a synthetic mobility model and we define an artificial world populated by heterogeneous agents who differ in their mobility. Simulations are conducted on a multi-agent programmable environment. Our experimental results clearly demonstrate positive correlations between agent mobility factors and percolation thresholds.

Keywords: Social network, Dynamics, Modelisation, Percolation theory, Simulation

1. Introduction

The issue of *information* flow through social networks has risen important modeling issues in different application domains of information science. Information flow can be considered from the point of view of either *diffusion* or *percolation*. In a *diffusion* process, the information is considered to be transmitted from an individual to his neighbours with a given probability while in a *percolation* process, the transmission is always achieved between two individuals but the stochastic mechanism is put on each individual neighbourhood generation. Studying percolation through a network helps finding thresholds that ensure the connectivity and the spreading of the information like a news or a rumor through the whole network. On the other hand diffusion allows to find conditions under which an information like a disease may be spread depending on different parameters such as the probability for an individual to get the information from another. *Network based approaches* have been intensively explored in information diffusion modeling and have proved their relevance to explain the impact of social links and social structures on disease transmission for instance. Most works in this field have explored static characteristics of networks but have not considered the role of *networks dynamics* until recently [2, 5].

1877-0509 © 2012 Published by Elsevier Ltd.
doi:10.1016/j.procs.2012.06.007

The general expression of *information* may represent either knowledge, rumor, diseases or numeric viruses for instance even if one can notice a particular emphasis on epidemics in researches on diffusion phenomena. Whatever is the kind of information, we can identify common trends in the propagation: an individual (a human being, an animal, a machine) switches from one given state like *ignorant* to another one like *spreader* according to its current stage and its neighborhood all along the spread process. This analogy is widely admitted and has been discussed in previous works. Modeling principles of dissemination are frequently based on state transitions of individuals. They usually consider two or three states: the initial state of an agent before he receives the information, a second when he has received the information, a third state can be introduced to figure that the agent has become indifferent regarding the information. For instance, in rumor spreading, individuals are commonly categorized as ignorant, spreader and stifler. In previous studies few attention has been paid on social agents *mobility* and its impact on network dynamics and on the information spread while mobility is obviously an important dimension transverse to any social practice. New societal challenges like urban planning or traffic management need to get a better knowledge of user motion patterns and user behavior in their environment. Synthetic *mobility models* like random walk models were mostly studied for designing mobile ad hoc networks (Manets) and communication protocols [1]. More recently, it has appeared concrete schemes that represent real user traces following similar patterns with cyclic spatio-temporal regularities.

In this paper, our objective is to demonstrate the impact of *agent mobility* on the *information flow through a social network*. In this first work, we focus only on the *percolation* process as a first stage. In this approach, the network dynamics is induced by mobility. Individuals are figured by agents and each one is characterized by his own mobility that represents his way to move. We show how much and why individual mobility may have an impact on (i) social behavior at the individual level and (ii) afterwards at global level on the information flow through social links when these links need spatio-temporal co-occurrence. Agent mobility may induce deep modifications in social links among agents and thus variations on the information spreading. The mobility that we have considered here is geographic and the social behavior is realized by the ability for an agent to have a direct contact *via* spatial proximity. We have defined a synthetic model, the *Eternal Return Model*, that dramatically reduces the real world complexity to a simple social behavior. Social links between agents are solely defined by direct physical contact and a physical contact is supposed to be induced by proximity only.

When an ignorant meets a spreader, he obtains the information and he becomes a spreader in his turn. Since the percolation process is only studied here, there is no probability of transmission between two agents, but the agent density variability induces the process randomness.

Despite its simplicity, this social behavior model gives a true interpretation of the real world where each individual has generally social contacts with only a closed and small fraction of the entire population. An agent is considered to have a *social contact* with another one if and only if this agent is located in his narrow neighborhood. While rather basic, this situation takes an important social meaning since it happens when roads are crossing and two people meet in a limited spatio-temporal space. In such a case, social relationships are rarely meaningless. Each one is likely to transmit an information to others standing in the same reduced space.

The remaining of the paper is organized in four sections: Section 2 is devoted to the ER model, in Section 3 we present the social network induced by the agent mobility, in Section 4 we present our results on the impact of agent mobility on the percolation process and in Section 5 we conclude.

2. The ”Eternal-Return” model of mobility

The *Eternal-Return* (ER) model defines a kind of *spatio-temporal mobility* that represents the way people behave when they move from place to place. Mobility is here considered as *circulation* that is motion of individuals like pedestrians in an urban or inter-urban space. The ER mobility model is defined in order to simulate the tendency of humans to return to the location they visited earlier. This mobility is typical of homework motions. More generally it is observed in real life experiments on human trajectories that are much restricted by street configurations and are in contrast with the smooth asymptotic behavior predicted for a random walk. People typically tend to follow predefined paths and to travel in similar patterns when moving through their urban environment [3].

Although the ER model of mobility is freely inspirited, and very restrictive, it is sufficient to express truly the fact that some agents go across large spaces while others are confined in a small areas: *sedentary* (resp. *travellers*) agents are characterized by low (resp. high) mobility. Each agent has its own location that is updated when he is moving forward. He has a *heading* that indicates the direction he is facing and he will follow to move straightforward. The agent heading is a value between 0° and 360°. At each time step, each agent moves straight on for one unit. Thereby the speed is constant and identical for all the agents. In each time-step-slice, we determine the new position for an agent on the basis of his current position and his mobility. Hereafter we detail the notion of mobility in ER and the principles of the simulations that have been run.

2.1. Agent mobility

The ER model defines agents trajectory as a regular polygon, with one vertex at each time-step. The amount an agent a_i turns at a corner is his constant *exterior angle* (noted α_i). Walking all the way round the polygon, an agent makes one full turn. The sum of exterior angles in his trajectory is equal to 360°. Let us note fTL_i (stands for $fullTurnLength$) the length of the path - polygon size- an agent a_i has to follow to come back to a given position. fTL_i is thus the number of time-steps needed to make one full turn. Moreover we assume each agent have his own direction d_i i.e. he walks around his polygon either clockwise or counter-clockwise: in the first case $d_i = -1$ otherwise $d_i = +1$. For each agent the $fullTurnLength$ is a fixed number in the range $[3, 360]$. Finally, we normalize this value by dividing it by its maximum value.

For each agent a_i, we define his mobility μ_i by the following equation:

$$\mu_i = d_i \cdot \frac{fTL_i}{360} \tag{1}$$

So the relation between the *mobility* and the *exterior angle* is:

$$\mu_i \cdot \alpha_i = 1 \tag{2}$$

With these hypotheses, mobility μ_i is a real number in the range $[-1, 0[\cup]0, +1]$, and the absolute value of the exterior angle α_i varies from 1° to 120°. As a consequence, the less mobile agents move on a tiny triangle and the more mobile agents move on a big polygon of 360 sides. The borderline case of mobility is for $\alpha = 0$ (i.e. $\mu = \infty$) and corresponds to a *linear trajectory*.

Algorithm 1 describes the ER mobility process: depending on its location and its mobility μ_i, each agent defines its own motion. Although in real life a same individual can live and travel in different regions defined for instance by home and workplace, we assume in the ER model a more simple situation where each agent has an invariable mobility. Agents walk around regular polygons and, as each one has the same speed, their only characteristic parameter is their mobility. As a consequence, the local behavior of each mobile agent is deterministic and periodic (see an illustration of agent trajectories on figure 1). As there are many agents, and so many periods which interact together, it is difficult to predict when and where agents will cross in a same vicinity.

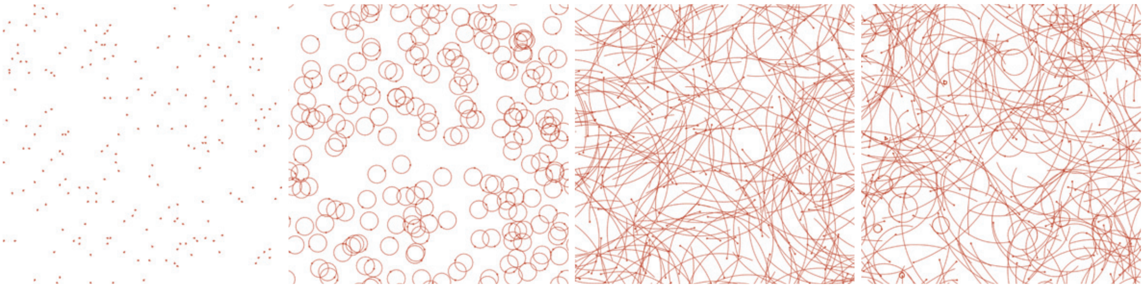
To clarify the terminology and allow to simplify the analysis, according to mobility, we define two typical class of agents: the *traveller* and the *sedentary* agents. In real life, a sedentary people inhabits the same locality throughout life and at the opposite, a traveller is a person who is frequently on a trip and moves around. Let us note that while the ER model requires only one specific parameter by agent, it is realistic to some extents since it can exhibit sedentary agents as travellers: sedentary agents (resp. travellers) are defined by low (resp. high) $fullTurnLength$.

2.2. Simulation

The Eternal-Return model has been implemented with the *NetLogo* multiagent programmable modeling environment [7][4]. The space is a 2-dimensional grid connected circularly so that the model is similar to a 2-D cellular automata model where the “world” includes numerous agents embedded on a toroidal grid.

Algorithm 1 MakeMove

{Make agents move according to their mobility}
for agent a_i in *agents* **do**
turn right by $\frac{1}{\mu_i}$ degrees
move forward for one step
end for



(a) (b) (c) (d)

Fig. 1. Agent's trajectory: *density* = 2%, at time 40
(a) no-mobility (b) $fullTurnlength = 20$ sedentaries (c) $fullTurnlength = 180$ travellers (d) mixed mobility

Simulations are performed on a $L_1 \times L_2$ lattice. The agent density δ is a parameter of the model[1]. There are $L_1.L_2.(1 - \delta)$ empty locations and $(L_1.L_2.\delta)$ agents. In order to ensure equivalent samples, whatever density is, simulations presented in this paper use a population of 1,000 agents and thus the world size is adapted accordingly to the density. At the initial step $t = 0$, agents are randomly distributed across the unbounded grid. The coordinates of unit areas (i.e. cells) are integers and agents coordinates are real numbers. Several agents may stand on a same cell at the same time. A *mobility* is assigned to each agent *via* its own $fullTurnLength$. All reported results are based on the mean of 100 runs. Algorithm 2 gives the general outline to simulate the Eternal-Return model.

Algorithm 2 Simulate the *Eternal-Return model*

$t \leftarrow 0$, $density \leftarrow \delta$
create $(L_1.L_2.density)$ agents
for agent a_i in *agents* **do**
initialize $fullTurnLength_i$ in $[3, 360]$
$\{\mu_i \in [-1, 0[\cup]0, +1]\}$
initialize the location $(x_i(0), y_i(0))$ at random
end for
loop
Call *MakeMove* {move agents according to their *mobility*}
$t \leftarrow t + 1$
end loop

3. Social links induced by mobility

In this section we study the system resulting from activating ER agent motions. Features are studied according to two points of view: (i) the underlying network, i.e. the resulting network of all distinct contacts

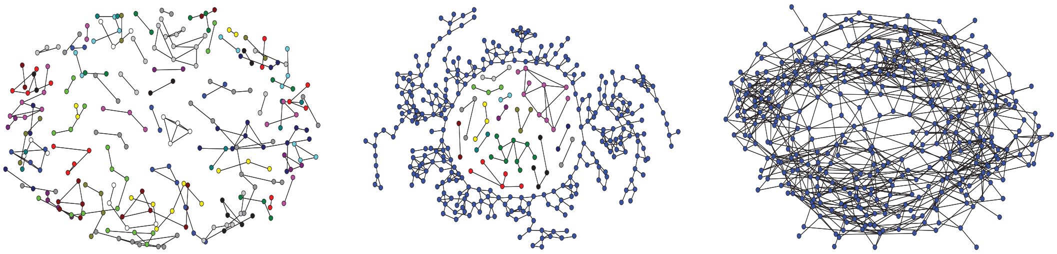
[1]For humans, the population density is the number of people per unit area

between agents and (ii) the distribution in the space, i.e. the agent attendance on cells when they are moving.

3.1. How mobility induces dynamic social networking

Social networks are structures gathering individuals (*nodes*) connected by one or more specific kinds of dependencies (*links*) with strong social meaning. Interdependencies can be of various natures such as friendships, common interest, sexual relationships, or relationships of beliefs, knowledge or prestige. In the ER Model, agents can be assimilated as nodes and their social links are generated by spatial proximity. This kind of interactions, based on geographical proximity of individuals takes on much interest since it is an abstract generalization of multiple effective contacts such as physical contact, exchange of words, participation in the same event or attendance at the same place. In epidemiology proximity networks have been most extensively studied to understand how various patterns of human contacts, induced by underlying social behaviors such as mobility, facilitate or not spreading process in a population.

Mobility is a core parameter in spatial agent-based models, because it sets the agent neighborhood configuration and so the ability for an agent to establish a contact with another agent. In the ER model, mobility allows agents to explore areas more or less important of their geographical environment and *a fortiori* to generate more or less proximity contacts as shown in the following section. Indeed, we suppose that two agents come into contact when they are geographically close enough, i.e. the proximity distance between them is less than or equal to 1. Mobility results in a network of contacts, which dynamics is a very significant feature, since each time agents are in motion, new contacts are created while others are deleted.



(a) (b) (c)

Fig. 2. The underlying network obtained with $density = 15\%$ for (a) $fTL = 3$ (b) $fTL = 10$ (c) $fTL = 20$. All nodes linked by the same color belong to the same component.

By the way, a new network is built as being the network of all distinct contacts between agents. It represents the maximum proximity contact network in which each individual is linked with all other he met during the simulation. Thus, at every instant, the instantaneous graphs of proximity contacts are sets of disconnected small graph clusters of the underlying network that represent current agents contacts. Obviously, this network is much denser than the instantaneous proximity contact graphs.

On Figure 2, three examples of this network obtained with $density = 15\%$ and fTL constant are depicted. All nodes linked by the same color belong to the same component. As expected, we can observe that mobility has a direct impact on the overall number of contacts, since the density of the network increases with fTL. In some extend, this network summarizes the dynamics since its properties give insight on the process of information spread. For example, we can observe (see Figure 2(a)) that too low mobilities may not guarantee its connectivity and indeed we will show that this gives a clue to the inability to percolate.

3.2. How many visitors per cell?

In the case of no-mobility when each agent stays forever in the same place, and if we assume no-superposition of agents, the number of visitors for a cell is either zero or one. Since agent distribution is random as stated in section 2, the mean number of visitors per cell is the density δ of agents in the world. In the case of mobility, when the agents move in the spatio-temporal space, the situation gets more complex. In such a case, the total number of agent-visitors for a cell may be obviously greater than zero and more, the no-superposition hypothesis does not match. For each cell c_i, let's note V_i the set of agents a_k that visit c_i, i.e. $V_i = \{a_k^i\}$; $\#V_i$ is the number of polygon-trajectories that intersect the cell c_i ; some cells may have no visitor whereas others have a lot.

In the particular case where mobility is identical for all the agents, data obtained by simulation allow to establish that, $\#V_i$ follows approximately a *Poissonal distribution*. The number of visiting agents $\#V$ on geographical areas follows a Poissonal distribution with a fast decaying tail: it is strongly peaked at $\#V=\langle V \rangle$ and it decays exponentially with $\#V$. The curve flattens when mobility increases: the peak value decays with mobility while $\langle V \rangle$ increases. For instance, if agents are sedentary ($fTL = 20$), numerous cells have few visitors while in the case of travelers ($fTL = 360$) much less cells have lots of visitors. This result provides a valuable argument to check the ER mobility model. Indeed, it was proved in geographic researches that data obtained as counts over geographic regions can be described by Poisson random distribution when individuals are independent with the same probability to occur and each region has the same probability to be attended [6].

We have conducted simulations in order to get the mean of the number of visitors per cell, $\underset{i}{mean}\,\#V_i$, versus the *density* for a given value of the $fullTurnLength$ (fTL = 360, 180, 90, 45 and 3). Each couple of result is averaged over 100 runs. We have observed a linear correlation between the two variables: the more the density of agents, the more the number of visitors. Experimental data have led to the following equation suggesting that the $\underset{i}{mean}\,\#V_i$ over all the cells is proportional to the product of the $fullTurnLength$ by the $density$.

$$\underset{i}{mean}\,\#V_i \approx 0.95 \times fTL \times \delta \tag{3}$$

Thus, if $\delta = \frac{k}{0.95 \times fTL}$, the mean number of visitors is on average closed to k.

This last result provides an additional evidence of conformance for the ER model. The linear dependency between $\underset{i}{mean}\,\#V_i$ and both density and mobility is indeed expected since with a constant fTL for all agents, each agent visits fTL cells, thus the number of visitors on a cell should be equal to $fTL \times \delta$. The 5% gap experimentally observed should be explained by co-occurrences of agents on cells. In the same way one can establish than standard-deviation is approximated by the square root: $\sqrt{0.95 \times fTL \times \delta}$.

Finally, we obtain:

$$P(\#V = k) \approx \frac{(-0.95 \times fTL \times \delta)^k \times e^{-0.95 \times fTL \times \delta}}{k!} \tag{4}$$

4. Mobility and Percolation process

The ER model and proximity contacts have been defined and built in order to understand how an information can be broadcast on the grid network when agents are in motion. The grid structure induces proximity and the agent mobility is a decisive parameter. The minimum limit case where all the agents have the smaller mobility, i.e. each one moves on a tiny triangle, is closed to the classical static case as each agent stays stuck in a very small region of the space.

For experiment relevance, one crucial condition on the grid structure is its ability to allow spreading for which the minimum agent density has to be determined. For that purpose, we have used the percolation theory to study the impact of mobility on spreading according to two kinds of parameters: (i) agent *density* (δ) on the grid and (ii) agent mobility (fTL). The *rumor spreading* context serves as a reference since it provides a concrete case in which the transmission is generally achieved between two persons in contact and it stays generic enough to be extended to other ones. We show the existence of a connectivity threshold needed to guarantee the communications in the network. This section details the simulations conducted and the experimental results obtained.

The percolation paradigm is widely used in spatially dissemination models. For instance, it allows to identifying epidemic thresholds for invasion, separating non-invasive regimes from invasive regimes. Invasion thresholds for host-parasite systems show marked transitions towards invasion. They define parameters values beyond which a given vertex belongs to an infinite open cluster. The phenomenon of percolation can be modelled as transforming a regular lattice into a random network by randomly "occupying" vertices with a statistically independent probability δ. Beyond a critical threshold δ_c, large clusters are built and the system is connected from one side to another: δ_c is called the *percolation threshold*. This critical value of the process on a square lattice was shown to be near 0.59.

However, this result is mainly limited to static agents. When mobility is introduced, the dissemination threshold is not proved. In the static case, the probability of invasion is controlled by a single parameter, the transmissibility of information between neighboring hosts that depends on the density of agents only. With the ER mobility model, the critical threshold, if any, depends on both density and mobility.

In our experiments, we assume that all agents have the same mobility and we examine how thresholds for invasion are influenced by the density of agents together with the effect of mobility. Thus we show that the percolation paradigm can be extended to the case of mobile agents. We assume that each individual can be in two discrete states, such as *no-yet-informed* or *informed*: all agents are initially in the *no-yet-informed* state except one randomly selected agent that is *informed*.

4.1. Percolation via spatio-temporal proximity

In this work, the strong assumption on proximity relies on its correlation with transmission. Indeed we consider proximity as the only condition allowing transmission. The rumor is spread thanks to *proximity*: an informed agent transmits the rumor to his nearest neighbors only. We have conducted experiments to determine the percolation threshold δ_c according to given values for mobility. We have deduced the value of the critical threshold δ_c as corresponding to a proportion of 50% infected agents. As expected, δ_c monotonously decreases from 60% to asymptomatically reach zero as mobility increases as shown on Figure 3. Let's note that this decrease is drastic as it falls from 60% for no-mobility to 5% for a yet small mobility with $fTL = 30$. As a consequence, we observe that the impact of mobility on the ability to propagate the rumor is tough. In this way, mobility magnifies the effect of local actions at global level. One intriguing finding is that the threshold δ_c follows an approximate *power-law* decrease according to the mobility. More precisely, the δ_c function of $fullTurnLength$ approximately obeys the form:

$$\delta_c(fTL) \approx 1.624 \times fTL^{-1.043} \tag{5}$$

This relation allows either to approximate the threshold of percolation knowing mobility or, conversely, for a given density, to compute the required mobility for percolation (see Figure 4). Intuitively, with mixed fTL, we may think that only few travellers should be necessary for the information percolates.

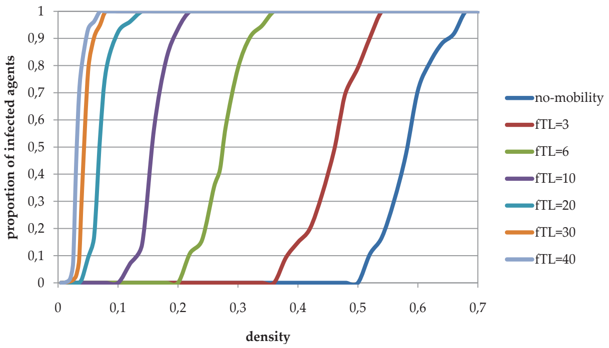


Fig. 3. Proportion of infected agents vs. *density*
From right to left: no-mobility and $fTL = 3, 6, 10, 20, 30, 40$

4.2. Percolation threshold versus Number of visitors per cell

Let's remember that the value $\frac{k}{0.95 \times fTL}$ for density corresponds to the case of k visitors by cell on average (see eq. 3). Whatever mobility is, the threshold of percolation δ_c is greater than $\frac{1}{0.95 \times fTL}$ and smaller than $\frac{2}{0.95 \times fTL}$ as illustrated by Figure 4). This means that the network percolates when the mean number of visitors per cell is a number between one and two.

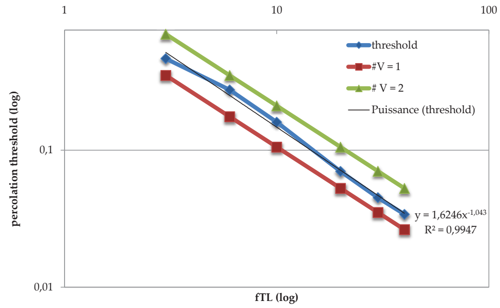


Fig. 4. Density (log) vs. fTL (log)

From bottom to top: $\#V = 1$ (red square), percolation threshold (blue diamond), $\#V = 2$ (green triangle)

5. Conclusion and future works

In this paper, we have addressed the problem of information dissemination on dynamic social networks. As a first stage in this study, we have focused on a percolation mechanism and the network dynamics has been induces by a synthetic model of mobility.

(i) We have proposed the ER model, a mobility model implemented as a multiagent system that allows agents to explore areas of their space according to individual rules. As a proof of validity, studies conducted on the ER model have shown that it reproduces real world patterns.

(ii) Then, we have shown how the ER model induces locally proximity contacts and results in a dynamic human contact network that can support various kinds of spreading phenomena such as information dissemination. In a first approach, we have shown how agent mobility has a direct impact on network connectivity.

(iii) Finally, we have extended the notion of percolation threshold to the mobility case. Extensive experiments have been conducted to understand how the dissemination process behaves according to agent mobility. The relationship highlighted between percolation threshold and agent mobility factor allows to deduce the minimum mobility for diffusion when density is fixed and *vice versa*.

The results obtained have practical implications for the analysis of information dissemination in general and in particular for the disease control strategies in more realistic systems.

As perspectives in a short term, we plan to investigate the impact of mobility on network features and explain whether mobility leads to topological patterns. A second track is the study of diffusion on the underlying network. In a long term, we hope our model will stimulate empirical and theoretical work, and provide a framework for analyzing the influence of all aspects of spatial human behaviors on diffusion processes.

References

[1] Tracy Camp, Jeff Boleng, and Vanessa Davies. A survey of mobility models for ad hoc network research. *Wireless Communications and Mobile Computing*, 2(5):483–502, 2002.

[2] Claire Christensen, István Albert, Bryan Grenfell, and Réka Albert. Disease dynamics in a dynamic social network. *Physica A: Statistical Mechanics and its Applications*, February 2010.

[3] Eric Daudé and Emmanuel Eliot. Exploration de l'effet des types de mobilités sur la diffusion des épidémies. In *Proceedings of Théo Quant'05.*, 2005.

[4] D. Pham. *From Agent-Based Computational Economics towards Cognitive Economics.* in Bourgine P., Nadal J.P eds : Cognitive Economics : An Interdisciplinary Approach. Springer verlag, 2004.

[5] Erick Stattner, Martine Collard, and Nicolas Vidot. Diffusion in dynamic social networks: Application in epidemiology. *22nd International Conference on Database and Expert Systems Applications*, 2011.

[6] J. Vaillant, G. Puggioni, L. Waller, and J.-H. Daugrois. A spatio-temporal analysis of the spread of sugar cane yellow leaf virus. *Journal of Time Series Analysis*, 32:396–406., 2011.

[7] U. Wilensky. Center for connected learning and computer-based modeling, 1999. http://ccl.northwestern.edu/netlogo/.