

# SIMPS: Using Sociology for Personal Mobility

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**Abstract**—Assessing mobility in a thorough fashion is a crucial step toward more efficient mobile network design. Recent research on mobility has focused on two main points: analyzing models and studying their impact on data transport. These works investigate the consequences of mobility. In this paper, instead, we focus on the causes of mobility. Starting from established research in sociology, we propose SIMPS, a mobility model of human crowds with pedestrian motion. This model defines a process called sociostation, rendered by two complimentary behaviors, namely socialize and isolate, that regulate an individual with regard to her/his own sociability level. SIMPS leads to results that agree with scaling laws observed both in small-scale and large-scale human motion. Although our model defines only two simple individual behaviors, we observe many emerging collective behaviors (group formation/splitting, path formation, and evolution).

**Index Terms**—Mobility modeling, self-organized networks, social networks, sociology.

## I. INTRODUCTION

**M**OBILITY modeling aims at describing in the most accurate and simplest way the motion of mobile entities. They are fundamental tools in a large variety of domains, such as physics, biology, sociology, networking, electronic gaming, and many others.

As of now, there is a growing number of mobility models used in the design and analysis of communication systems, but how many of them fully represent the aspects characterizing the mobility of human beings? This is a fundamental issue, since in many situations the mobility of communicating and sensing equipments follows human mobility. In this paper, we specifically address this question.

Mobility modeling refers in general to the Random Waypoint model (RWP) [1], which is the *de-facto* standard for both theoretical analysis and simulation studies. RWP belongs to the same class as Brownian motion, also called random walk, and has the main advantages of being simple and analytically tractable. Nevertheless, the simplicity provided by RWP fails in capturing realistic behaviors observed in human mobility, as shown by a number of recent studies [2]–[5]. Fortunately, great advances have been recently achieved toward more realistic mobility models since the networking community has decided

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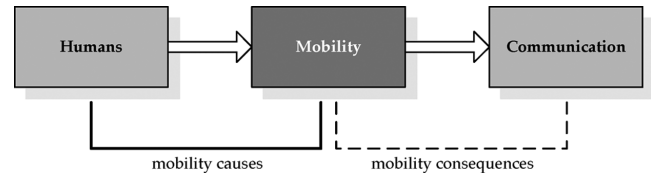


Fig. 1. Our approach on mobility causes.

to investigate mobility in a finer level of details. A first set of models is based on expectations of how mobility is performed in particular situations such as first proposals of campus [3] and vehicular mobility models [4], [6]. Another set of proposals tweak RWP parameters with specific distributions in order to yield more realistic results [5], [7].

Recent mobility measurements performed both indoor and outdoor [8], [9] enabled the proposal of trace-based models calibrated with empirical data [10]–[12]. Furthermore, a number of analyses show that both contact and inter-contact distributions [8], [9], [13], [14], as well as location popularity distribution [11], follow power-laws. They also allowed revisiting the realness of existing models. For example, measurements have confirmed the presumption that RWP is unable to realistically model human mobility, since it leads to exponential distributions for both contact and inter-contact times. Another impact of measurement-based studies is that it is now possible to reassess mobility model assumptions. For example, in the valuable work done by Grossglauser and Tse [15] on the beneficial aspect of mobility on communication networks, the authors assumed i.i.d. random placement of nodes; but, as has been observed in a study by Tudeuce and Gross [11], this is not necessarily the case.

Despite the increasing number of works questioning the effective role of mobility, two main issues remain unanswered:

- *Lack of explanation of the process governing mobility.* Should RWP be used to represent a worst-case scenario or the uncorrelated displacement of individuals using different transport facilities? In order to represent more specific scenarios, a number of models have simply embedded realistic and higher level features and rules to RWP [3], [16]. Yet, neither advance evidences that they captured realistic displacements.
- *Retained modeling methodology.* Recent proposed models [7], [11], [17] have been designed to artificially match a very limited set of empirical observations. No clear methodology is applied to evaluate the proposed mobility models.

We argue that a far deeper investigation of the roots governing mobility is necessary toward realistic mobility modeling (Fig. 1). Instead of simply replaying observed mobility patterns, we propose to rely on well established theories that tackle the natural process which govern mobility at its roots. The consequence is the lifelike emergence of mobility characteristics found in measurements; this is contrary to current approaches where these characteristics are artificially generated. To this end,

we revisit the way human mobility modeling is done by tackling its causes and no more trying to match its consequences.

The characteristic of that approach is very important, since we consider mobility by its causes. While we will study the characteristics outputted by our mobility proposal throughout its parameter set, and compare them with characteristics recorded from mobility traces, our goal here is clearly not to gauge the consequences of our work in terms of routing performance (consequences). Such a study is out of the scope of this paper. However, we are currently carrying out an extensive study based on the methodology proposed in [18] in order to compare the outcome of SIMPS with real traces from the iMote experiments [8].<sup>1</sup>

In this paper, we propose SIMPS (Sociological Interaction Mobility for Population Simulation), a mobility model aimed at pedestrian crowd motion that explores recent sociological findings driving human interactions: (i) each human has specific socialization needs, quantified by a target social interaction level, which corresponds to her personal status (e.g., age and social class [20], [21]); (ii) humans make acquaintances in order to meet their social interaction needs [22], [23]. In this paper, we show that these two components can be translated into a coherent set of behaviors, called *sociostation*, driving the dynamics of simulated entities.

For the calibration and validation of the model, we compare the simulation results with empirical observations obtained from measurements referenced previously. Our results show that SIMPS leads to the same laws observed in recent empirical results. This is the basis for a high confidence in the validity of the model.

The remainder of this paper is organized as follows. In Section II, we present some background required for the definition of our model. In Section III, we detail the SIMPS model and its parameters. Then, in Section IV, we present an extensive analysis of SIMPS parameters. In Section V, we describe the methodology used for the tests performed and discussed in Section VI. In perspective of this analysis, further points are discussed in Section VII. Finally, in Section VIII we conclude this work.

## II. RATIONALE

In the following, we give the required background to understand our proposal. We first start by describing the modeling approaches we have retained. We then reconsider the way collective motion in mobility can be modeled. Eventually, we describe the sociological basis upon which our approach relies.

SIMPS adopts a mobility modeling approach centered on behavioral rules. Behavioral mobility models rely on continuously interacting rules that express atomic behaviors governing mobility. Such an approach finds great success in other domains such as physics and artificial intelligence. SIMPS defines two behavioral rules, namely socialize and isolate. These rules express recent sociological findings driving human interactions [20]–[23]. Of course, no model can realistically integrate all potential behaviors that drive human motion. In fact, human beings are driven by many interacting influences, needs and motives driven by schedules and social ties, to cite a few. Hence, our goal is to (i) rely on realistic sociological assumptions (ii) with

<sup>1</sup>On a sidenote, the reader can refer to [19] for a routing-oriented taxonomy of mobility consequences.

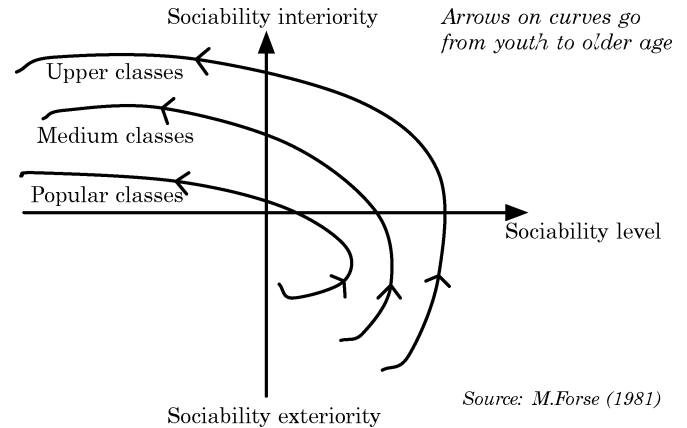


Fig. 2. Evolution of the sociability of humans. As can be seen, the characteristics of one's sociability are dependent on intrinsic personal characteristics, such as social class and age, instead of, e.g., the situation the person is in.

a reduced set of behaviors (as simple as possible) (iii) still exhibiting recent distributions observed empirically.

A crucial point in modeling human mobility is to characterize collective behaviors. The current approach to group modeling does not go further than proposing correlated motion as in RPGM [24] and leaves open the processes behind group composition (merges) and group splits. SIMPS responds to these limitations by having emerging collective behaviors results of the social interactions driven by our two rules. The difficulty is now to find 'realistic' assumptions of social interactions.

We base our proposal on the following findings. The first finding, *intrinsicity*, has been expressed concurrently in the literature by several research papers [20], [21]. It states that the sociability level of a given person is intrinsic to each person, and strongly dependent on internal factors (e.g., social class and age). In this paper, we define a one's *socialization* as the current state of her/his social contacts with other humans, and one's *sociability* as her/his usual socialization will. This means that each individual has its own and constant sociability level at a given period in life that does not depend on its place in a social network—contrary to what one could assume—as shown by Fig. 2. This sociability level is translated to a need for social interactions.

The second finding, *interactivity*, is derived from a socialization behavior defined in [22], [23], that assesses that individuals' aim to fulfill their sociological interaction needs. This can be expressed by building new social ties until the needs are fulfilled or by satisfying these needs by encountering acquaintances. These acquaintances are defined by individuals to whom an individual is tightened in a social network.

These two findings let us define a principle, which is that the intrinsicity of an individual's socialization is maintained through her interactivity. This principle is called *sociostation*. Inherently, sociostation means that an individual will permanently adapt her measure of socialization to her own desired (intrinsic) sociability, by the way of her actions.

In this paper, we will translate this sociostation into the domain of pedestrian mobility. Although many other influences are at play in any individual's mobility, such as collision avoidance, activity planning and constraints, we wish here to gauge the effect of this process alone, aside from any other influence. Simulating complete pedestrian mobility is therefore out of the

scope of this paper. The reader is invited to refer to a companion paper of the same authors, which addresses pedestrian mobility [25].

In aforementioned works [20], [21], socialization is rated in level and quality. In this work we concentrate on the socialization level alone, and do not assess the socialization quality. The socialization level is here defined as the number of persons an individual is in social contact with. According to proxemics [26], we consider that the existence of an immediate social contact between two individuals is dependent on the spatial distance separating the individuals considered at that point in time.

As will be seen in the next chapter, the process resulting from the translation of sociostation into the domain of mobility will make use of a social network. Social networks have already been used to design mobility models such as the ones proposed by Musolesi *et al.* [12], [27]. In these authors' proposal, individuals are gathered in clusters by a heuristic which processes a graph representing social ties. Each cluster is then affected to a specific region in space. Mobility is generated by individuals moving from region to region according to a preferential attachment process.<sup>2</sup> Although both models share two common aspects, namely social graphs and its use in decision taking, they differ in their fundamentals and expression. This point will be the subject of discussion in the next section.

### III. SIMPS: AN INTERACTION-BASED MOBILITY MODEL

#### A. Overview

SIMPS is a translation of sociostation in the domain of human motion: each individual will try to regulate her socialization to her own sociability (intrinsicity) by the effect of her actions (interactivity). To this effect, we need: (A) a sociability level, intrinsic to each individual, around which he/she regulates her socialization, represented by the number of individuals a node would like to be surrounded by (cf. Section III-B); (B) a measure of socialization, or level of social interaction, at the individual scale; (C) a sufficient set of actions effecting on the individual's socialization; (D) a local decision process to use these actions in effectively regulating socialization as desired.

At the scale of a simulation, we assume: (i) fixed social interaction need per individual (intrinsicity) and (ii) fixed social graph representing social ties between individuals.

The interactions with acquaintances and non-acquaintances can be translated into a behavioral model. From these behaviors, defined by rules, individuals join and leave acquaintances. In SIMPS, each individual is associated with a personal sociability (A). This individual's sociability is the equilibrium point of a social interaction she/he tries to achieve all the time. Each individual is also associated with a context-aware indicator, namely perceived surround (B), which indicates the individual's perception of her current socialization volume; basically, this value depends on the number of surrounding individuals.

In order to meet the desired sociability level, individuals can resort to two complementary behaviors used in turns (C):

<sup>2</sup>In a graph, this process specifies that incoming nodes create links with already present ones, with a probability proportional to the latter's degree. While extremely simple, this process generates graphs with a scale-free node-degree distribution. Another work that makes direct use of the preferential attachment principle, but directly translated to mobility, is available in [28].

*socialize*—movements toward acquaintances—and *isolate*—to escape from undesired presences. The acquaintances of an individual are determined by the social graph in which acquaintances are represented by directed edges, the absence of edge denominating strangers. The effects of socialize and isolate behaviors are, respectively, to raise and lower one's perceived surround. To activate one of these behaviors, a behavior decision process (D) estimates, continually and for every individual, her current socialization volume, and compares it to the individual's own needs.

With this model, we do not pretend to represent all types of human mobility by assuming that the movement of people is simply based on a mechanisms of moving towards some people or avoiding them. We model (with simple assumptions) only the social component of mobility, which might be more or less important depending on the context. An example where it has major influence on the behavior of individuals is the experience of Chaintreau *et al.* that measured contact and inter-contact times between participants at a conference [8]. This is a typical case where movements are mainly dictated by acquaintances.

SIMPS is composed of two parts: *social motion influence* and *motion execution unit*. The social motion influence updates an individual's current behavior to either socialize or isolate. The *motion execution unit* is responsible for translating the behavior adopted by an individual into motion. We detail these processes in the following.

#### B. Social Motion Influence

SIMPS simulates the dynamic properties of a population  $\mathcal{P}$  containing  $N$  individuals in a two-dimensional plane. Time  $\tau$  is assumed to be discrete, with steps of  $\Delta\tau$ .

We define now a number of variables that represent the behavior of an individual. Although some of these variables will be used only in Section III-C, we prefer to introduce them in the following to assure a more natural explanation of the model.

Individual  $i \in \mathcal{P}$  tends to socialize at her own volume, plus or minus a certain variation. This defines the following two random variables:  $s_i$ , or the *personal sociability* of node  $i$ , is the number of individuals that node  $i$  aims at being surrounded by.  $t_i$ , or the *tolerance level* of node  $i$ , is the fractional tolerance in the position of the perceived surround relatively to the personal sociability for which the individual still feels comfortable.

Following these random variables, we can define  $i$ 's *social comfort range*, the range of perceived surround (measure of socialization volume) she/he feels comfortable with:

$$z_i = [s_i(1 - t_i), s_i(1 + t_i)]. \quad (1)$$

According to the theory of proxemics [26], the social awareness of an individual is situated in a geometric sphere around her, whose radius  $R_{\text{soc}}$ , namely *social distance*, is approximately 3.5 meters, or 12 feet (cf. Section IV). In this sphere, the perception of nearby individuals is not immediate, i.e., individuals progressively notice the presence of others. The perceived surround is based on this fuzzy perception and is noted  $u_i$ . In order to reproduce this fuzziness in SIMPS, individual  $i$ 's perception is rendered by a pseudo-control loop as shown in Fig. 3. In this loop, the perceived surround  $u_i$

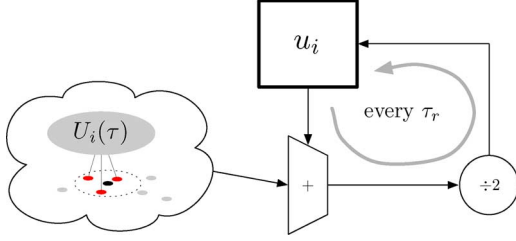


Fig. 3. Pseudo-control loop for the computation of the perceived surround (measure of socialization volume).

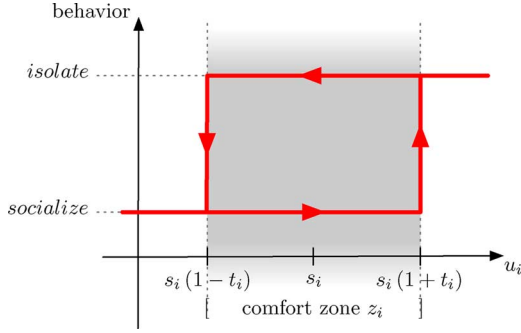


Fig. 4. Sharp hysteresis curve for individual  $i$ 's behavior decision process.

is periodically mixed with  $U_i(\tau)$ , which gives the number of individuals within  $i$ 's social sphere at time  $\tau$ . The period of the pseudo-control loop is called *half-perception time* and noted  $\tau_r$ .

We can now give expressions that determine the values of the different variables. Individual  $i$ 's surround is updated every  $\tau_r$  seconds as follows:

$$u_i = \frac{U_i(\tau) + u_i}{2} \quad (2)$$

where  $U_i(\tau)$  is given by

$$U_i(\tau) = \sum_{\substack{j=1 \\ j \neq i}} P_{i,j}, \quad \text{where } P_{i,j} = \begin{cases} 1, & \text{if } |\vec{i}j| \leq R_{\text{soc}} \\ 0, & \text{otherwise.} \end{cases} \quad (3)$$

In (3),  $|\vec{i}j|$  denotes the Euclidian distance between nodes  $i$  and  $j$ .

The perceived surround  $u_i$  serves as input to the feedback decision process, which updates the behavior of the individual according to a sharp hysteresis as shown in Fig. 4. This hysteresis depends on both the individual's sociability  $s_i$  and tolerance level  $t_i$ . Individuals should initially start with a neutral *a priori* about their situation. To this effect, for any individual  $i$ , we have  $u_i = t_i$  at  $t = 0$  and their initial behavior is to socialize.

### C. The Twin Social Behaviors

As in existing work, including the one of Musolesi *et al.* [12], SIMPS relies on social graphs from which motion influence behaviors are derived. Social graphs do not represent physical proximity, but only relationships among individuals. Nevertheless, the former influences the latter, since close acquaintances tend to get physically closer.

In SIMPS, a social graph  $G = (V, E)$  is oriented and non-Eulerian. Vertices represent the nodes in the topology. Links, valued in the range  $[0;1]$ , represent the acquaintances felt from

its origin node toward its destination node: zero means no acquaintance at all (i.e., the destination is stranger to the origin) while one means high acquaintance (i.e., the destination has the maximum social proximity with the origin).<sup>3</sup>

The *acquaintance* felt by  $i$  toward  $j$  is expressed as

$$A_{i \rightarrow j} = \begin{cases} f(l_{i \rightarrow j}), & \text{if } l_{i \rightarrow j} \in E \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

where  $f(l_{i \rightarrow j})$  is the weight of edge  $l_{i \rightarrow j}$ .

The *alienness*  $\overline{A}_{i \rightarrow j}$  felt by  $i$  toward  $j$  is defined as

$$\overline{A}_{i \rightarrow j} = 1 - A_{i \rightarrow j}. \quad (5)$$

We can now precisely define the *twin* behaviors of nodes:

**Definition 1 (Socialize):** Individuals are attracted by acquaintances. The attractive tension  $\vec{\eta}_{a_{ij}}$  felt by  $i$  toward  $j$  is a vector collinear to  $\vec{i}j$ , whose magnitude is proportional to the acquaintance  $A_{i \rightarrow j}$  and inversely proportional to a power  $\lambda_f$  of the distance  $\|\vec{i}j\|$ :

$$\vec{\eta}_{a_{ij}} = \frac{\vec{i}j A_{i \rightarrow j}}{\|\vec{i}j\|^{\lambda_f + 1}}. \quad (6)$$

**Definition 2 (Isolate):** Individuals are repulsed by strangers. The repulsive tension  $\vec{\eta}_{r_{ij}}$  felt by individual  $i$  toward any other individual  $j$  is a vector collinear to  $\vec{j}i$ , whose amplitude is proportional to the alienness  $\overline{A}_{i \rightarrow j}$  and inversely proportional to a power  $\lambda_f$  of the distance  $|\vec{i}j|$ :

$$\vec{\eta}_{r_{ij}} = \frac{\vec{j}i \overline{A}_{i \rightarrow j}}{\|\vec{i}j\|^{\lambda_f + 1}}. \quad (7)$$

The  $\lambda_f$  parameter is called *distance fading exponent*.

As explained in Section III-A, SIMPS models the social component of mobility, which is believed to play a major role in driving mobility in many situations. This is demonstrated in works by Fleury *et al.* [18] analyzing the dynamical and social features of mobility traces collected by Chaintreau *et al.* [8] in the iMotes experiments.

**Resulting Motion:** Nodes are either in socialize or isolate mode (as described in Section III-B). When in socialize mode, we have that  $\vec{\eta}_{i,j} = \vec{\eta}_{a_{ij}}$ . On the other hand, when in isolate mode, node  $i$  applies  $\vec{\eta}_{i,j} = \vec{\eta}_{r_{ij}}$ . The vectorial sum  $\vec{\eta}_i = \sum_{i \neq j} \vec{\eta}_{i,j}$  of all attractive or repulsive tensions give the direction of the willingness,  $\vec{w}_i$ , of  $i$ 's *social motion influence* [as depicted in Fig. 5(a) and (b)]:

$$\vec{w}_{i,\tau} = \begin{cases} \hat{\vec{\eta}}_i e_{i,\tau}, & \text{if } |\vec{\eta}_i| \neq 0 \\ \vec{0}, & \text{otherwise} \end{cases} \quad (8)$$

where  $e_{i,\tau}$ , called  $i$ 's *excitation*, is given by

$$e_{i,\tau} = \max\left(\left|\frac{u_i - s_i}{s_i t_i}\right|, 1\right). \quad (9)$$

The excitation is null when  $i$  feels surrounded at her exact sociability need  $s_i$ , and progressively increases until attaining

<sup>3</sup>Observe that the social graph does not have to be complete.

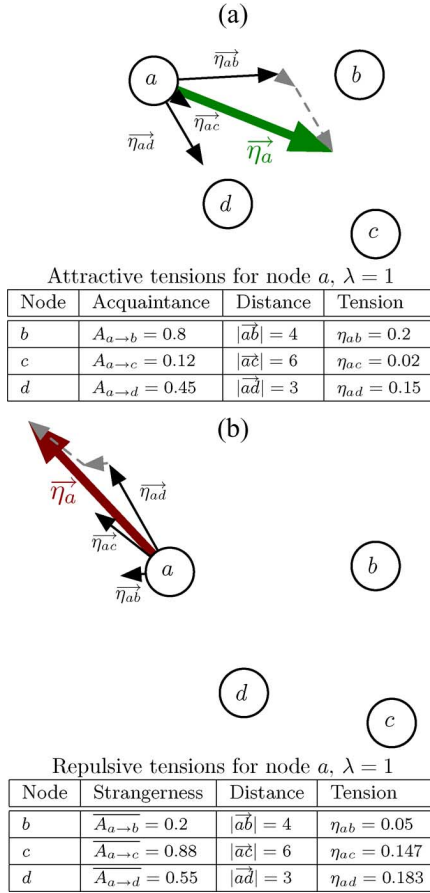


Fig. 5. Illustration of the tension computation process when the individual presents either socialize or isolate behaviors. (a) Socialize behavior. (b) Isolate behavior.

1, when  $i$ 's surround  $u_i$  falls outside  $i$ 's comfort range  $z_i = [s_i(1 - t_i), s_i(1 + t_i)]$ .

A special instance of (8) happens when the sum of tensions is a null vector. Typically, this refers to situations where an individual is attracted toward or repulsed in many directions at the same time with a neutral result. In this situation, the individual hesitates and does not update her/his velocity, continuing in a straight line (motion management is detailed in the following Section III-D). This situation, which is quite rare, is a case of unstable equilibrium. The fact that (i) neighboring individuals move and (ii) the individual's own motion takes him/her away from this situation, makes this situation very short-lived. Some very specific equilibrium situations would still theoretically be feasible, but they would involve that the entire interacting population be simultaneously in this status, and was moving at the exact same velocity when it happened, and they would only work in periodic space. This very particular case is extremely unlikely, and while we managed to obtain it doing a lot of tentative runs with two and even three nodes, we have never encountered it with a more significant population counts. In fact, given its dependence on a collective equilibrium, the probability for this "stuck" situation to happen drops exponentially with the number of nodes,<sup>4</sup> rendering it virtually inexistent in runs with more than four individuals.

<sup>4</sup>If the probability of a node to have a null vector is  $p$ , the probability of  $n$  nodes to have a null vector is  $p^n$ . Here we have  $p < 1$ , thus  $p^n$  decreases exponentially with  $n$ .

Another point to consider is that this willingness (in fact acceleration) may not lead to a definite individual at all times. This particular possibility is also experienced by flocking mobility models based on the seminal work of Reynolds for bird and fish schools in 1987 [29]. The flock model has become the reference basis for animal herd AI in games and movies, and is considered the most realistic.

Works of Musolesi *et al.* [27], [30] also make use of some kind of preferential attachment and weight by the inverse of distance (of which gravitational attraction also makes use). The originality in SIMPS resides in its twin behavior (socialize and isolate) and their interplay. In its expression, SIMPS combines gravitational attraction and preferential attachment. Regarding previous uses of these two effects to mobility, the reader is also invited to refer to a companion paper by a subset of the same authors [28].

#### D. Motion Execution Unit

The social motion influence is not the sole parameter to have an impact on human motion. The role of the *motion execution unit* is to comply with two basic parameters governing the physical motion of individuals: velocity and acceleration. A more complete set of parameters (e.g., collision avoidance or terrain diversity) could be implemented; however, in order to focus on the social aspect of mobility, we only consider velocity and acceleration.

Velocities and accelerations are distributed according to two random variables, respectively  $V$  and  $A$ , whose characteristics will be discussed later on. Individual  $i$  is associated with an acceleration request,  $\vec{a}_{r,i,\tau}$ , which is proportional to  $i$ 's social motion influence:

$$\vec{a}_{r,i,\tau} = a_{\max i} \vec{w}_{i,\tau} \quad (10)$$

where  $a_{\max i}$  denotes the maximum scalar acceleration individual  $i$  tolerates.

The acceleration request is applied with respect to  $i$ 's maximum velocity  $v_{\max i}$ . Given  $i$ 's velocity vector at time  $\tau - \Delta\tau$ ,  $\vec{v}_{i,\tau-\Delta\tau}$ , and the direction  $\vec{a}_{r,i,\tau}$  of the acceleration request, we compute the maximum acceleration  $a_{\lim i,\tau}$  that can be applied for a duration  $\Delta\tau$  without trespassing  $v_{\max i}$ . Since SIMPS discretizes time  $\tau$  in steps of  $\Delta\tau$ , we have

$$\vec{v}_{i,\tau} = \vec{v}_{i,\tau-\Delta\tau} + \vec{a}_{i,\tau} \Delta\tau \quad (11)$$

and the speed limit condition

$$|\vec{v}_{i,\tau}| \leq v_{\max i} \quad (12)$$

which gives us the acceleration limit

$$a_{\lim i,\tau} = \frac{\sqrt{v_{\max i}^2 - \left( |\vec{v}_{i,\tau-\Delta\tau}| \times \left| \sin(\widehat{\vec{a}_{r,i,\tau}, \vec{v}_{i,\tau-\Delta\tau}}) \right| \right)^2}}{\Delta\tau} - \frac{|\vec{v}_{i,\tau-\Delta\tau}| \times \cos(\widehat{\vec{a}_{r,i,\tau}, \vec{v}_{i,\tau-\Delta\tau}})}{\Delta\tau}. \quad (13)$$

TABLE I  
PARAMETERS USED BY SIMPS

| Name              | Relates to       | Type             | Description                    | Value                            |
|-------------------|------------------|------------------|--------------------------------|----------------------------------|
| $S$               | Sociability      | Random variable  | Sociability of individuals     | $N(\mu = 2.5, \delta = 1)$       |
| $N$               | Social graph     | Integer variable | Number of nodes/individuals    | $\in \mathbb{N}$                 |
| $D$               | Social graph     | Real variable    | Average node outdegree         | $\in [0; N - 1]$                 |
| <i>Graph type</i> | Social graph     | Enumerated value | Graph type                     | in {Natural, Random, Scale-Free} |
| $R_{soc}$         | Human perception | Real variable    | Social radius                  | 3.5 meters                       |
| $\tau_r$          | Human perception | Real variable    | Half-perception time           | 4 seconds                        |
| $\lambda_f$       | Human perception | Real variable    | Distance fading exponent       | $\in [0; 3]$                     |
| <i>Space</i>      | Space            | Enumerated value | The space where motion happens | in {Infinite, Periodic Square}   |
| $L$               | Space            | Real variable    | Size of periodic shape         | $\in [0; +\infty[$               |
| $\tau_{max}$      | Time             | Real variable    | Total time considered          | $\in [0; +\infty[$               |
| $\Delta\tau$      | Time             | Real variable    | Time quantization step         | $\in [0; \tau_{max}[$            |

The acceleration request is then satisfied at best by the final acceleration  $\overrightarrow{a_{i,\tau}}$ :

$$\overrightarrow{a_{i,\tau}} = \hat{\overrightarrow{a_{r,i,\tau}}} \times \min\left(|\overrightarrow{a_{r,i,\tau}}|, a_{lim,i,\tau}\right) \quad (14)$$

which is used to update  $i$ 's current velocity  $\overrightarrow{v_{i,\tau-\Delta\tau}}$  and position  $\overrightarrow{p_{i,\tau}}$ :

$$\begin{cases} \overrightarrow{v_{i,\tau}} = \overrightarrow{v_{i,\tau-\Delta\tau}} + \overrightarrow{a_{i,\tau}}\Delta\tau, \\ \overrightarrow{p_{i,\tau}} = \overrightarrow{p_{i,\tau-\Delta\tau}} + \overrightarrow{v_{i,\tau}}\Delta\tau. \end{cases} \quad (15)$$

#### IV. EVALUATION

Table I summarizes the parameters that are internal to the SIMPS mobility generator. They are described in the following.

##### A. Pedestrian Motion Characteristics

This parameter dictates the distributions of the random variables  $V$  and  $A$ , respectively the velocity and acceleration of individuals. According to results published by Henderson in [31], velocity  $V$  for pedestrians is set to follow a normal law  $N(\mu = 1.34, \delta^2 = 0.26)$ . To our knowledge, there is no empirical study on human acceleration. Thus, we set it to follow a normal distribution  $N(\mu = 1.3, \delta^2 = 0.4)$  (which assumes that humans switch from immobile position to walking in the order of a second).<sup>5</sup>

##### B. Social Interactions Characteristics

These characteristics govern the interactions between individuals. Random variables  $S_i$  and  $T_i$ , introduced in Section III-B govern the distribution of instances  $s_i$  and  $t_i$  which denote, respectively, the volume of social interaction (sociability) required by each individual  $i$  and the variation she/he tolerates on this volume of interaction (tolerance). This volume is closely related to the number of neighbors an individual has in its surrounding. Studies of Henderson in [31] show that group size distribution of pedestrians in various contexts follows a truncated Poisson law ( $\lambda_g = 2.5$ ) of positive discrete values. Since the sociability distribution,  $S_i$ ,

<sup>5</sup>Tests have shown that the acceleration value does not change our results. We are aware however that this is an important issue especially in the context of micro-mobility but this is not our primary focus here.

in SIMPS is a continuous function, we translate this discrete Poisson law into a normal law  $N(\mu, \delta^2 = 1)$ <sup>6</sup> with  $\mu$  being the variable parameter under study. Furthermore, the tolerance on this sociability is set to a uniform distribution in  $[0.1; 0.7]$  (i.e., between 10% and 70% tolerance on the sociability).

The social graph defines acquaintances between individuals, which are used to compose the twin behaviors. This graph is parameterized by the number of nodes  $N$ , the average node degree  $D$ , and the type, which can be natural (when drawn from real traces) or synthetic (e.g., Erdős–Rényi random graph, exponential node-degree distributed graph, or Albert–Barabási scale-free graph with power-law node degree distribution).<sup>7</sup> The average node degree for various measured social graphs varies more than one order of magnitude depending on the subject of the social graph. For example, sexual contact graphs exhibit a low average node degree ( $D \approx 2$ ), followed by phone calls graphs ( $D \approx 3$ ), blogs ( $D \approx 14$ ), up to actor collaboration ( $D \approx 61$ ).

##### C. Human Perception Characteristics

Human perception defines the parameters that affect the way human beings perceive their environment. They are in number of three: social distance, half-perception time, and distance fading exponent. The value of these parameters depend mainly on the mobility context (e.g., car driving, conference, school playground) and cultural variations.

Looking at social distances, Proxemics, defined by E. T. Hall [26], stipulates that relations between humans are dependent on the distance separating them. The social distance is the physical distance under which social transactions and interactions occur. In the U.S., this distance was measured to be around 12 ft. (or 3.5 m); however, this value was found to vary from about half to several times this distance, depending on cultural variations, and also on spatial constraints, such as typically crowded areas. In SIMPS, this value is directly translated into  $R_{soc}$ , the distance used for one's current socialization estimation. While 3.5 m is the typical value we set for our tests, we also investigate the impact of its variations.

<sup>6</sup>These laws are not exactly equivalent, but this is the closest form we can find in literature.

<sup>7</sup>No existing graph model precisely captures the characteristics of social networks. For this reason, we have performed simulations using different underlying graph structures. These simulations have shown that the distributions of contact and inter-contact are invariant regardless of the graph model used (cf. Section VI-A).

The half-perception time  $\tau_r$  regulates the pseudo-control loop described in Section III-B. It describes the time an individual takes to perceive changes in her neighborhood. Although, to our knowledge, this parameter has not been much investigated, research on car driving show that the perception time may range from hundreds of milliseconds to tens of seconds [32], [33]. Yet, the current available literature does not study the context of pedestrian motion, at which SIMPS is targeted. As we will show in the next section, SIMPS's results remain consistent within the range between 1 and 20 seconds. For the remainder of our study, and considering a more relaxed environment than car driving, we empirically set  $\tau_r = 4$  s for our simulations.

Eventually, the distance fading exponent  $\lambda_f$  (cf. Section III-C) plays an important role to represent the cost an individual associates to the distance separating her from another individual. This cost depends on the mobility scenario under consideration. For instance, individuals in a conference are more prone to displace to meet acquaintances than in a camping. This cost can in fact be represented by the notion of attraction and more generally by a gravity law. Basically, when  $\lambda_f = 1$ , it means that the distance has a first order impact on the result (the cost of a motion is considered linear to the distance), while  $\lambda_f = 2$  means that the distance has a second order impact (the cost is considered to be in square of the distance). We will investigate the effect of  $\lambda_f$  in Section VI.

#### D. Spatial Characteristics

This parameter describes the space in which individuals move. The boundary conditions can be of three types: infinite, finite, and periodic. If finite, the topology can be a square, a disc, or any kind of bounded geometric space. If periodic, the topology can be a square (with toroidal boundary mapping). In the remainder of this paper, we investigate the properties exhibited by SIMPS alone. We will focus on the infinite and periodic square (toroidal mapping) cases, in which the influence of square side  $L$  will be investigated. The reason for this choice is to have a periodic space and avoid any border effects. In this way, we can investigate movements of crowds when they tend to infinity, independently of any mechanism for managing the environment (e.g., walls, obstacles). These latter can be, if needed, included in the simulator, but this is out of the scope of this paper.

#### E. Time Characteristics

Time characteristics concern the total duration  $\tau_{\max}$  for which motion is considered, and the time quantization step  $\Delta_\tau$  used for motion rendering. These two values, although more related to implementation than to model definition, are of prime concern since their choice can directly influence the outcome of the synthesized motion. It is then of major importance to distinguish inherent characteristics of our model from eventual bias due to time sampling. In the analysis below, we explore the effects of time quantization and total considered duration on the results of SIMPS.

### V. METHODOLOGY

In this section, we wish to highlight the outcome of our approach, which comforts recent observations of power-laws. The most common observation of power-law distributions lies in the

contact/inter-contact durations. It is exhibited by studies conducted on WiFi-enabled devices at Dartmouth [9] and UCSD [10]. Recently, a specific set of experiments conducted by Cambridge University, U.K., in collaboration with Intel, traced the contact and inter-contact duration distributions between mobile users carrying iMotes Bluetooth devices [8]. Although at a lower communication scale than previous studies, the three experiments conducted in [8] (all three at different times and locations, and with different users) showed strikingly similar observation of the power-law distributions<sup>8</sup> of human contacts. Contact and inter-contact durations have been observed to follow power-laws whose exponents were situated respectively around  $-1.5$  and  $-0.6$ , with exponential cut-offs. In Section VI-F, we show that such cut-offs are due to the finiteness of observations as well as some other reasons. For example, Karagiannis *et al.* [14] provide an analytical explanation for this observation based on the derivation of random walks. They further demonstrate these models can be representative of real mobility.

In order to investigate social interactions between individuals, we simulate human mobility with conditions similar to [8]. In the iMotes experiments, users carried Bluetooth-enabled devices, which periodically recorded the presence of other Bluetooth-enabled devices, such as other iMotes, PDAs, mobile phones, or laptops. A contact situation between individuals was asserted as soon as the presence of one node was felt by the other one, and an inter-contact asserted as soon as two or more consecutive measures did not show the presence of a previously seen node. The theoretical range of Bluetooth is around 10 meters. We consider however that a more realistic 6-meter range is a valid assertion for sensing range in most situations. In this way, we chose to simulate a simplistic range-based contact condition based on a maximum distance of 6 meters separating individuals.

While we wish to understand how SIMPS behaves through its different parameters, we focus on the metrics that are closely related to mobility observations, namely contact and inter-contact outcomes. Looking at the impact of SIMPS on routing protocols would also be an interesting work to conduct, but similar performance on routing-dependent metrics would not permit to deduce a similarity in the underlying mobility models with any specific confidence. In this regard, the goal of this paper is not to gauge the impact of SIMPS on routing protocols.

## VI. RESULTS AND DISCUSSION

Tests on the outcome of SIMPS mobility regarding contact and inter-contact distributions have been conducted over a population of  $N = 100$  individuals. The general parameters used by SIMPS are shown in Table II while the different values of the simulations we conducted are depicted in Table I.

#### A. Influence of Social Graph

The first aspect to gauge is the effect of the underlying graph structures on the behavior of the model. To this effect, the distributions of contact and inter-contact durations of Bluetooth-carrying nodes subject to SIMPS mobility are plotted,

<sup>8</sup>Power-law distributions of the CCDF are a characteristic watermark of scale-free phenomena. Still, this is not a systematic implication.

TABLE II  
SUMMARY OF TEST SETTINGS

| Aspect            | $\Delta_\tau$ | $\tau_{max}$    | $\langle S \rangle$ | Graph type  | $D$            | $\lambda_f$  | $R_{soc}$             | Space    | $L$              | $\tau_r$    |
|-------------------|---------------|-----------------|---------------------|-------------|----------------|--------------|-----------------------|----------|------------------|-------------|
| Social graph type | 1s            | 3600s           | 2.5                 | [Random,SF] | 5              | 1            | 3.5m                  | Periodic | 200m             | 4s          |
| Avg. node degree  | 1s            | 3600s           | 2.5                 | Scale-Free  | [2, 5, 15, 50] | 1            | 3.5m                  | Periodic | 200m             | 4s          |
| Sociability       | 1s            | 3600s           | [1, 2.5, 10]        | Scale-Free  | 5              | 1            | 3.5m                  | Periodic | 200m             | 4s          |
| Socialize only    | 1s            | 3600s           | 2.5                 | Scale-Free  | 5              | 1            | 0                     | Periodic | 200m             | 4s          |
| Isolate only      | 1s            | 3600s           | 0                   | Scale-Free  | 5              | 1            | $> \sqrt{2} \times L$ | Periodic | 200m             | 4s          |
| Social distance   | 1s            | 3600s           | 2.5                 | Scale-Free  | 5              | 1            | [1, 3.5, 15]m         | Periodic | 200m             | 4s          |
| Reaction time     | 1s            | 3600s           | 2.5                 | Scale-Free  | 5              | 1            | 3.5m                  | Periodic | 200m             | [1, 4, 20]s |
| Distance cost     | 1s            | 3600s           | 2.5                 | Scale-Free  | 5              | [0, 1, 2, 3] | 3.5m                  | Periodic | 200m             | 4s          |
| Space: infinite   | 1s            | 3600s           | 2.5                 | Scale-Free  | 5              | 1            | 3.5m                  | Infinite | $\infty$         | 4s          |
| Space: periodic   | 1s            | 3600s           | 2.5                 | Scale-Free  | 5              | 1            | 3.5m                  | Periodic | [20, 200, 2000]m | 4s          |
| Total duration    | 1s            | [600s, 1h, 10h] | 2.5                 | Scale-Free  | 5              | 1            | 3.5m                  | Periodic | 200m             | 4s          |
| Time quantization | [0.1, 1, 10]s | 3600s           | 2.5                 | Scale-Free  | 5              | 1            | 3.5m                  | Periodic | 200m             | 4s          |

for both random and scale-free graphs,<sup>9</sup> in Fig. 6(a). As we can observe, the contact and inter-contact duration distributions follow power-laws in both cases, and with very close exponents. The distribution of inter-contact is a bit below the one of the scale-free graph, while contact duration distributions are very close for both graph structures. All these distributions experiment an exponential cut-off around 500 s but this cut-off, clearly marked in the inter-contact distributions, is much fainter in the contact distribution. As stated previously and demonstrated later in Section VI-F, these cut-offs are due to the finiteness of the observation period.

We also verify that after the cut-off the distribution follows an exponential decay. This appears precisely when plotting the same distributions on a semi-logarithmic scale [Fig. 6(b)], where the exponential decay appears as a straight line.

The similarity of the mobility patterns obtained with scale-free and random (exponential) graphs is noticeable, and both correspond to the same power-law of exponent  $\alpha = 1.2$ . Inter-contact distributions are also very similar for both graph types, with a slightly sharper cut-off for the scale-free social graph. We conclude from this that the graph structure has minor influence relatively to the emergence of the power-law contact and inter-contact distributions. This result is very important and surprising: *although social graph are notable for their power-law degree distribution, power-law contact and inter-contact distributions are not due to this feature, and emerges from the social motion.*

The average node-degree  $D$  of the social graph can vary significantly depending on the scenario. We verify then how SIMPS behaves under different average node degrees. Tests have been run for four different values of  $D$ : 2, 5, 15, and 50. These values span a broad range of situations encompassing most social graphs studied in literature. The results are plotted in Fig. 6(c). We observe that contact and inter-contact distributions remain quite stable in their power-law nature, despite the important changes in the underlying social graph. The exponents in both distributions tend to increase slightly in function of  $D$ .<sup>10</sup>

<sup>9</sup>e.g., Albert–Barabási scale-free graph with power-law node degree distribution and Erdős–Rényi random graph with exponential node degree distribution.

<sup>10</sup>Notice the extreme case where  $D = 50$  and a node is, in average, an acquaintance of half the whole population. In this case, the inter-contact distribution tends to a Weibull form. This tendency can also be found in UCSD [10] and Dartmouth [9] studies.

The two previous observations give us high confidence in the robustness of SIMPS, and its reasonable independence relatively to the social graph used. For this reason, we decide to use Albert–Barabási scale-free social graphs for the remainder of this paper. These are considered to be closer to real social graphs than Erdős–Rényi random graphs. The default value for  $D$  will be 5.

### B. Influence of Sociability

The next parameter we must verify for a social model is the variation of the social influence. We performed tests for three different values of  $\langle S \rangle$  ( $\langle S \rangle = \mu$ ), the first moment of random variable  $S$  representing the volume of social interaction. Results are shown in Fig. 6(d). We can see from the graph that although the slopes of both distributions change with the settings, their nature remains as a power-law with cut-off. For larger values of  $\langle S \rangle$ , in which humans have higher needs for socialization, the inter-contact distribution changes the most. This is an important phenomenon that we will explore hereafter: the power-law nature of both distributions outputted by SIMPS seems strictly dependent on the balanced presence of *both* socialize and isolate behaviors.

### C. Separate Effects of Socialize and Isolate Behaviors

We evaluate now the contribution of each of the twin social behaviors on mobility. To this end, we set the model for three runs. The first considers only the socialize behavior, the second considers only the isolate behavior, and the third considers both behaviors together. Setting a single behavior is accomplished by changing  $R_{soc}$ , the social distance (defined in Section III-B). Setting  $R_{soc} = 0$  means that individuals always want to socialize. Setting  $R_{soc} > \sqrt{2} \times L$  and distributing  $S$  and  $T$  so as no individual tolerates a surround of more than  $N-1$  individuals imposes that all individuals will feel over-socialized and want to isolate. The corresponding results are shown in Fig. 6(e).

We can observe from the graph the clear influence of the isolate behavior on the power-law distribution for both contact and inter-contact distributions. It is however not sufficient to explain the strong exponent difference between these two distributions, characteristic of all observations. The outcome of the socialize behavior is by far the more interesting—inter-contact distribution is far below contact distribution, and follows two power-law sections separated by a sudden decrease. Such a staircase-like

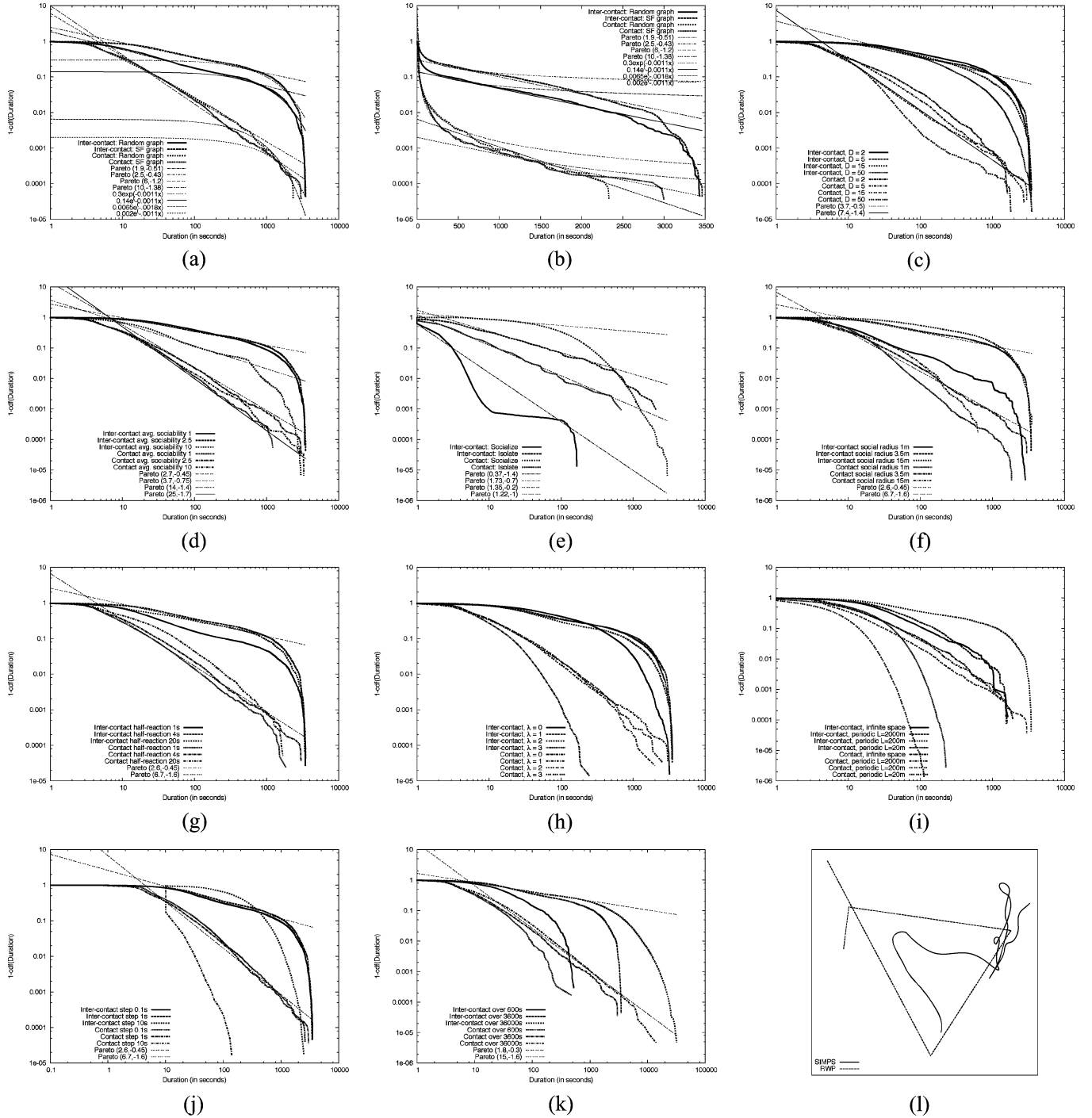


Fig. 6. Effect of various parameters on the outcome of SIMPS mobility [except 6(l)]. Contact and inter-contact duration distributions (6-m range). (a) Social graph: scale-free versus exponential. (b) Semi-log view of 6(a). The exponential decay appears here as straight lines. (c) Average node degree  $D$ . (d) Average sociability  $S$ . (e) Separate effect of *socialize* and *isolate* behaviors. (f) Social radius  $R_{\text{soc}}$ . (g) Half-perception time  $\tau_{\tau}$ . (h) Distance fading exponent  $\lambda_f$ . (i) Considered space (type and size). (j) Time quantization step  $\Delta_{\tau}$ . (k) Total duration considered  $\tau_{\text{max}}$ . (l) Trajectories: SIMPS, RWP.

feature could explain the presence of two smaller bumps barely visible as an outcome of SIMPS, and also present in various real-life measures, such as in [8]. In order to ensure that these bumps were not the result of the periodic space used, an additional run has been performed in an infinite space. Results exhibit the same characteristic. Another interesting emergent behavior is that, although individuals are most of the time in socialize mode, the global outcome of SIMPS tends more toward the characteristics exhibited by the isolate behavior. This seems

to indicate that the mixture of both behaviors is very different from their average, hence pointing the emergence of a different mechanism from their interplay.

#### D. Influence of Human Perception

1) *Social Distance*: Human perception also has direct influence on mobility. As discussed earlier in this paper, the typical social radius  $R_{\text{soc}}$ , or social distance between human beings was found to be around 3.5 meters for U.S. citizens [26], subject to

variations depending on sociocultural background (e.g., smaller in Latin countries, larger for rural areas) and context (e.g., reduced in crowded areas, sport events). In order to assess the effect of perception on mobility, a test has been run with three different values of  $R_{\text{soc}}$ : 1 m, 3.5 m, and 15 m. The results are shown in Fig. 6(f).

As seen with the case where  $R_{\text{soc}}$  is reduced to 1 m, contact and inter-contact duration distributions still show a power-law feature with cut-off, but with a higher exponent. When  $R_{\text{soc}}$  is raised to 15 m, both distributions experience a slight decrease in its exponent; however, the cut-off arrives much sooner in the contact distribution. This might be due to border effects, when the size of the social sphere approaches the total space considered for mobility (as we will see in Section VI-E). While interesting for our study, it is unlikely that this extreme case happens in reality, since proxemics states that the variation of social distance is related to the context an individual is immersed into; for instance, social distance is reduced in crowded areas.

2) *Half-Perception Time*: We now investigate the impact of how quick human beings perceive changes in their immediate surroundings. We performed tests with three possible values of the half-perception time,  $\tau_r$ : 1 s, 4 s, and 20 s. The results are shown in Fig. 6(g).

Although all values of  $\tau_r$  lead to close results, we note two tendencies. On the one hand, when perception time is minimal, the inter-contact distribution exhibits lower values, but more frequently. This is in part due to the fact that individuals rapidly try to escape from crowds and come back to meet acquaintances. A similar observation can be drawn for the contact distribution, but with lower impact. On the other hand, when perception time is at the longest bound, inter-contact distribution does not change that much, while contact distribution shows a neat decrease in the proportion of shorter contacts.

It finally appears that the half-perception time of 4 s (chosen for the rest of our simulations) does not lead to any of the border effects observed above. It results in strict power-laws and clear distinction between contact and inter-contact distributions, which are closer to the results obtained by Chaintreau *et al.* [8].

3) *Distance Fading Exponent  $\lambda_f$* : One of the particularities of physical motion is that each movement has a cost. In SIMPS, this is taken into account by the distance fading exponent,  $\lambda_f$ , which is used by each individual to weight the interest of meeting/avoiding another individual relatively to the distance separating them.

In SIMPS, individuals have explicit knowledge of other's behavior.  $\lambda_f$  can also be raised, in order to take into account an additional loss of influence with distance, optionally modeling a loss of probability of knowing another's whereabouts with increasing distance.

We ran tests with four different values of  $\lambda_f$ : 0 (distance has no influence on attraction between individuals), 1 (distance plays linearly), 2 (distance plays as a square), and 3 (distance plays as a cube).<sup>11</sup> The results are shown in Fig. 6(h). The main outcome of these tests is that when distance is not taken into account ( $\lambda_f = 0$ ), mobility is mainly characterized by a Weibull distribution, instead of a power-law. While still showing scale-

invariance in time, Weibull distributions are less characteristic of empirical traces, which tend more to a power-law.

Furthermore, the order at which distance is used in cost estimation does not fundamentally change the outcomes of SIMPS. The results indicate that distance plays a direct role in human displacement decisions, confirming results shown in [28].

### E. Influence of the Simulation Space

Individuals present different mobility characteristics depending on the space they evolve in. We have two parameters defining motion space. The first one, namely space type, defines if individual evolve in finite, infinite, or periodic space. In the case of limited space, the second one defines two options that manage the situation where individuals attain a border: (i) nodes stop when they face a border (obstruction); (ii) nodes' directions are symmetrically reflected against limits (reflection). In periodic spaces, these latter are considered as a torus—nodes escaping one border are replaced in the opposite border of the space. This model has the advantage of leading to regular average spatial density.

In addition to the experiments described earlier in this paper, which ran over periodic spaces, we also consider the case of infinite space. The goal is to investigate if our observations still hold. In addition, in the case of a non-infinite space, we also consider the impact of the density on the results, since it directly influences the equilibrium between the quantities of socializing and isolating individuals. We vary density with the inverse square of side  $L$ . The first run is performed in free-space, with users initially uniformly disposed in a square of 200 m on side, while the other simulations are performed in a periodic square space with sides varying between 20 m and 2000 m. The results are shown in Fig. 6(i).

The first observation is that in the free-space case contact and inter-contact distributions exhibit very close power-laws. This is a reminiscent characteristic of the isolate behavior—individuals can take the entire place they want. Looking at the runs with periodic space, the evolution of the distributions suggests a specific value of density that corresponds to the point of equilibrium between socialize and isolate behaviors. Above this point, the results tend to an exponential law, which is an inheritance of the RWP model. This is probably due to the fact that individuals move quickly from a point to another, and all the conditions change dramatically from one simulation step to another, rendering senseless the decisions of social adaptation. Below the point of equilibrium, the results obtained with a periodic space tend to approach the ones of free space.

### F. Influence of Considered Time

The influence of time on SIMPS outcomes appears in two ways: time quantization step and total simulation time. The first aspect is related to the very common problem of sampling on measurements. It can be summarized in one simple question: "Is the considered time step fine enough for a realistic view of the system?" To explore this issue, we ran three tests, with times quantization steps of 0.1 s, 1 s, and 10 s, respectively. The results are shown in Fig. 6(j).

It is straightforward to observe that the results with  $\Delta_\tau = 0.1$  s and  $\Delta_\tau = 1$  s are very close to each other, while  $\Delta_\tau = 10$  s

<sup>11</sup>Note that  $\lambda_f$  can also take real values in SIMPS expression.

completely changes the results. We can consider then with confidence that a time discretization step of 1 s is fine enough for the results we wish to observe. Such a time granularity is in accordance with the half-perception time of  $\tau_r = 4$  s we identified in our earlier experiments, and with the precept that a human goes from steady-state to full motion or inversely in around 1 s (recall that this value was used for acceleration distribution).

The second important aspect related to the influence of time is the total duration of the simulation. The fundamental question here is: “Do these observations extend with time considered, or are they limited in scale?” Again, three tests were conducted, with total durations of  $\tau_{\max} = 600$  s,  $\tau_{\max} = 3600$  s, and  $\tau_{\max} = 36\,000$  s. The results are shown in Fig. 6(k). As expected, the cut-offs are shifted right or left depending on the duration of the simulation. This hence demonstrates that (i) the observation period directly influences the cut-off in the tail of the distributions<sup>12</sup> and (ii) comforts theoretical results that mobility contact and inter-contact distributions are purely power-law in essence.

## VII. FURTHER DISCUSSION

### A. About Complex Systems Modeling

The main discussion relative the modeling of complex systems lies in the differences between two approaches.

- Simple models with mathematically tractable equations should be preferred whenever possible, since their use allows obtaining strict results and deterministic predictions.
- More complex models, on the other side, often tend to be non-deterministic and mathematically intractable.

The advantages in terms of “realism” of the latter approach is often considered dubious, when simpler models might render similar predictions. Indeed, a complex model is only interesting when it explores situations to which deterministic models cannot apply. With these considerations in mind, we aimed at making SIMPS as simple as possible, though exhibiting complex emerging features. Although SIMPS could be made more complex and specialized in many manners (for example, by introducing a third behavior stating that an individual just pauses at some location), we believe that such additions would restrict the scope of our results. Such adaptations, however, are welcome in more specific situations.

We also believe that SIMPS brings novelty in two ways: (i) it adapts outer knowledge from sociology that has not been used before and (ii) it generates mobility patterns that generate contact and inter-contact statistics both exhibiting scaling laws similar to recent observations.

### B. About Complex Behavior Emergence

The combination of very simple interacting rules leads sometimes to very complex outputs. Such an emergence phenomenon can be observed for instance via the SIMPS front-end interface (a real-time graphical interface of the simulator). We can observe for example situations referred to as *bugger’s case*: an

isolating node closely pursued by a socializing node. This appears as pairs of nodes having a highly asymmetric social relation.<sup>13</sup> Further observations showed that such situations resolve themselves since they are part of a more complex collective mechanism.

SIMPS also breaks the barrier between individual and group mobility: collective motion emerges in this model, without the help of explicit grouping.

### C. Trajectory Aspect

While we consider that a comparative study of SIMPS and RWP is out of the scope of this paper, we provide here an example of the patterns outputted by both of these models, for informative purposes. Fig. 6(l) shows the trajectories of two sample individuals (one having SIMPS mobility, the other having RWP mobility) during 3 mn. Both models have a speed set around  $1.5 \text{ m}\cdot\text{s}^{-1}$  and the time granularity of both synthesis is of a half second. The pause time for RWP is chosen in the interval [0 s;10 s]. All other parameters for SIMPS are set with standard values used throughout simulations above. The size of the area is a square 100 meters in side.

## VIII. CONCLUSION

In this paper, we proposed SIMPS, a mobility model that addresses the roots of mobility. SIMPS deals with sociological influences in human crowd motion found in typical situations like malls, fairs, cafeterias, clubs, beaches, or fora. SIMPS’s modular conception separates motion influences from motion generation, which allows associating additional mobility influences with little effort, e.g., pause time and obstacle avoidance. Based on a human feature thoroughly studied in sociology, namely sociability, SIMPS defines two behaviors that regulate each individual’s social interaction level.

We evaluated SIMPS using a simple in-range contact model. Under the light of recent measures of contact and inter-contact duration distributions, we draw the following surprising conclusions from our study.

- Although entirely synthetic, SIMPS’s traces show strong similarities with various heavy-tailed distributions observed in real-life situations.
- Such heavy-tailed features are emergent. While SIMPS uses a social graph for estimating motion, we show that the graph structure has negligible influence on the results. Decomposing the influence of the graph into two complementary behaviors, namely socialize and isolate, we show the crucial role of their interplay in the final mobility pattern.
- Depending on the input parameters, we found that the distributions expressed by SIMPS vary between power-law with exponential cut-off and Weibull form for the inter-contact duration statistics, and between power-law and exponential for the contact duration statistics. Power-law and Weibull distributions, while different, are both scale-free.

<sup>12</sup>A subset of the authors are currently analytically demonstrating this conclusion.

<sup>13</sup>Such examples can be further observed in recorded videos and traces of SIMPS motion, freely available on the SIMPS webpage at <http://www-tp.lip6.fr/~borrel/SIMPS>.

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