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### **A More Realistic Random Direction Mobility Model**

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#### **Abstract**

Mobility models are widely used in the simulation-based performance analysis of mobile networks. However, there is a trade-off between simple parametrization and realistic movement patterns. Synthetic models like the random waypoint and random direction model are simple to implement, but they only provide unrealistic simple user sojourn densities and traffic flows. In contrast, graph- or trip-based mobility models are complex to parameterize and their results are difficult to compare. In this paper, we propose the location-dependent parameterization of the random direction model to fill this gap. This model extension allows to setup non-homogeneous mobility scenarios, in particular based on real-world traces, while it still belongs to the class of synthetic random walk mobility models. We show that the location-dependent parametrization can accurately model arbitrary mobility patterns with very limited implementation complexity.

#### **Keywords**

mobility modelling; random mobility model; random direction model; simulation study

#### **Working Group 2**

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## Abstract

Mobility models are widely used in the simulation-based performance analysis of mobile networks. However, there is a trade-off between simple parametrization and realistic movement patterns. Synthetic models like the random waypoint and random direction model are simple to implement, but they only provide unrealistic simple user sojourn densities and traffic flows. In contrast, graph- or trip-based mobility models are complex to parameterize and their results are difficult to compare. In this paper, we propose the location-dependent parameterization of the random direction model to fill this gap. This model extension allows to setup non-homogeneous mobility scenarios, in particular based on real-world traces, while it still belongs to the class of synthetic random walk mobility models. We show that the location-dependent parametrization can accurately model arbitrary mobility patterns with very limited implementation complexity.

## 1 Introduction

The aim of user mobility models in mobile communications research is to enable communication protocol and system simulations in order to measure their performance. This is equivalent to the intention of traffic models in classical telecommunications research. To accomplish this task and to allow to obtain statistical valuable results, the models have to fulfill certain properties. Typically they have to

- generate realistic load situations,
- be stationary,
- be uncorrelated,
- have adjustment parameters to generate different load situations.

Modeling real-world user behavior is a challenging issue and often a trade-off between complexity and usability. One approach is to observe the mobility patterns in real systems. However, in practice such traces are not very useful for simulation studies since they only reflect one specific scenario that cannot be generalized. Furthermore they hardly fulfill the criteria of stationarity since real world scenarios typically have time dependent variations, e.g., regular commuters streams. As a consequence, many analytical and simulation-based studies of wireless networks are based on synthetic models that provide random mobility patterns. An overview on existing synthetic models can be found in [1,2].

Synthetic random walk mobility models are simple to implement in simulation tools and can be characterized by a small number of parameters. Two frequently used examples are the random

waypoint (RWP) and the random direction model<sup>1</sup>(RD). However, these models do not reflect real human mobility and provide homogeneous or at least very simple user densities only. For the performance evaluation of many advanced protocol mechanisms in mobile networks, e. g., pico-cells or vehicular networks, it is not very useful to assume homogeneous sojourn densities. Instead, more realistic mobility models are required which include, for instance, *attraction points* with a higher sojourn density, or directed *flows* of users.

Recently, several proposals have been made to provide more realistic movement patterns. They can be roughly subdivided into two categories: Some approaches are based on trip and activity models. They restrict users mobility to a certain graph, i. e., they only allow movements on predefined paths. Examples for such models are [3, 4, 5]. However, parameterizing such models based on real-world trace data is challenging and cannot be totally automatized [5], and their properties are difficult to compare. The other solution is to extend the existing synthetic random mobility models. For example, [6] proposes adding attraction points to the random waypoint model. More generally, [7] suggests to use different distributions for destination point, speed and pause duration in the random waypoint model, dependent on the starting point of a movement.

In this paper, we show that a location-dependent parameterization of the random direction mobility model can be used to get non-homogeneous movement patterns. This can be achieved by partitioning the simulation plane into non-overlapping regions and using different user mobility parameters in each of these regions. This usage of conditional distributions is quite generic and allows to setup very different scenarios with simple means. We originally developed this idea in [8] independent from [7]. Unlike [7], we use the random direction model as basis, since this model is better suited to be parameterized based on data from real-world traces. In this paper, we also show that our extension to the random direction model can be used to emulate other mobility models with limited complexity.

The remainder of this paper is structured as follows: In section 2, we motivate and introduce the location-dependent random direction model. In section 3, two examples of the model parameterization are presented and discussed to show qualitatively the capabilities of this models. Since manual editing only provides a limited degree of realism, we describe in section 4 a method to generate parameterizations for our model automatically as generalization of trace data, e. g., real-world traces. We show that our model can not only create complex non-homogeneous sojourn-density scenarios, but it also allows to emulate other mobility models. Finally, section 5 concludes the paper and provides an outlook to future work.

## 2 The Model

### 2.1 Existing Random Direction Models

The random direction mobility model is, besides the random waypoint model, probably the most widely used synthetic mobility model for mobile communications research. As well as the RWP model, this model considers individuals moving on straight walk segments with constant speed and optional pauses between walk segments. There are several flavours of the random direction model which slightly differ in the way they obtain the next walk segment. Hong and Rappaport [9] propose a model that is build on top of a cell structure and apply walkers that pass those cells on straight lines and choose new directions at cell borders. Guérin [10] extends this model in a way that direction changes can be performed anywhere in a walk area. Some approaches model the direction choice with absolute angles while others like the one proposed by Zanoози [11] calculate with relative changes to the current direction.

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<sup>1</sup>Sometimes random direction mobility models are also denoted as random walk models. Recently, there is a trend to utilize “random walk model” as generic term for entity based random mobility models while “random direction model” and “random waypoint model” denote specific mobility models according to how the next point of a walk polygon is selected.

In the following, we use the basic schema of point-to-point walks on straight lines with constant speed and optional pauses between two walk segments as depicted in figure 1. The parameters of a walk segment with index  $i$  starting at  $\vec{x}_i = (x_i, y_i)$  are the absolute angle  $\varphi_i$ , the length  $l_i$ , the speed  $v_i$ , and the pause at the beginning of the walk segment  $t_{p,i}$ . Thus the next waypoint  $\vec{x}_{i+1}$  reached at  $t_{i+1}$  is

$$\begin{aligned}\vec{x}_{i+1} &= \vec{x}_i + \vec{e}(\varphi_i) \cdot l_i \\ t_{i+1} &= t_i + t_{p,i} + l_i/v_i\end{aligned}\quad (1)$$

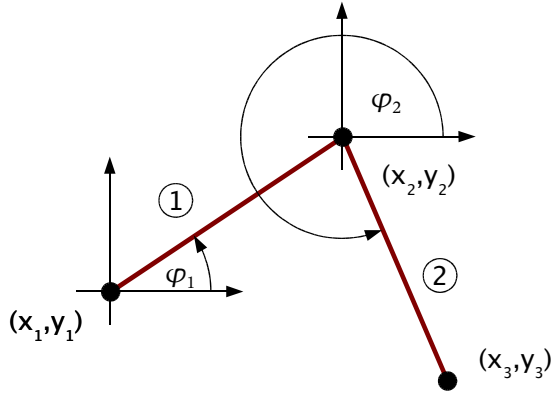


Figure 1: Walk segment definition of a random direction walk polygon

The standard parameterization of a RD walker is to treat the parameters for a walk segment as random variables (RV) with following uniform distributions:

$$\begin{aligned}\varphi_i &= \Phi & : & \text{Uniform } [0, 2\pi] \\ l_i &= L & : & \text{Uniform } [L_{min}, L_{max}] \\ v_i &= V & : & \text{Uniform } [V_{min}, V_{max}] \\ t_{p,i} &= T_p & : & \text{Uniform } [T_{p,min}, T_{p,max}]\end{aligned}\quad (2)$$

This way, the parameterization is reduced to the choice of the parameters  $L_{min}$ ,  $L_{max}$ ,  $V_{min}$ ,  $V_{max}$ ,  $T_{p,min}$ , and  $T_{p,max}$ .

## 2.2 Characteristics of the Standard Random Direction Model

In the random direction model, the sojourn density in a walk area of size  $A$  generated by one walker following this model is  $\rho(\vec{x}) = 1/A$  for the whole walk area and the mean user movement is zero since all movement directions are equal and nullify themselves (see section 3.1 for more details). These properties make this model attractive for simulation studies of mobile networks since the placement of cells and hot-spots within the walk area doesn't affect the simulation results. A drawback of the RD model is that a border behavior model is required that specifies the reaction of users reaching the simulation area boundary. Typically, a border behaviour complicates analytical approaches to the model since it introduces non-linear calculations that have to be covered by case discussions. There are different strategies such as wrap-around, bounce back or delete and replace [1].

## 2.3 The Random Direction Model with Location Dependent Parameterization

In this paper we propose a random direction model with location dependent parameterization (RD-LDP) which extends the RD model by making the random variables  $\Phi$ ,  $L$ ,  $V$ ,  $T_p$  dependent on the location where a new walk segment starts or a pause has to be made:

$$\begin{aligned}\varphi_i &= \Phi(\vec{x}_i) \\ l_i &= L(\vec{x}_i) \\ v_i &= V(\vec{x}_i) \\ t_{p,i} &= T_p(\vec{x}_i)\end{aligned}\tag{3}$$

One solution to realize this location dependency are modifications of the standard model using steadily defined distribution functions. For example, hotspots can be obtained by introducing a preferred direction in addition to a non-uniform distribution function as formulated by the equations (4) and (5). In this example, the well known gravity formula with masses  $m_i$  at attraction points  $\vec{p}_i$  and a walker mass  $m$  at its current waypoint location  $\vec{x}$  is used to determine a preferred direction

$$\vec{f}(\vec{x}) = \sum_{k=1}^K \frac{G \cdot m_k \cdot m}{|\vec{p}_k - \vec{x}|^2} \cdot \frac{\vec{p}_k - \vec{x}}{|\vec{p}_k - \vec{x}|},\tag{4}$$

from which the next direction  $\varphi_i$  is derived. Some randomness can be added by adding a normal distribution with the parameters  $\mu$  and  $\sigma^2$ :

$$\varphi_i = \arccos(\vec{f}(\vec{x})) + \text{Normal}[\mu, \sigma].\tag{5}$$

An example configuration using this kind of model creation can be found in figure 2.

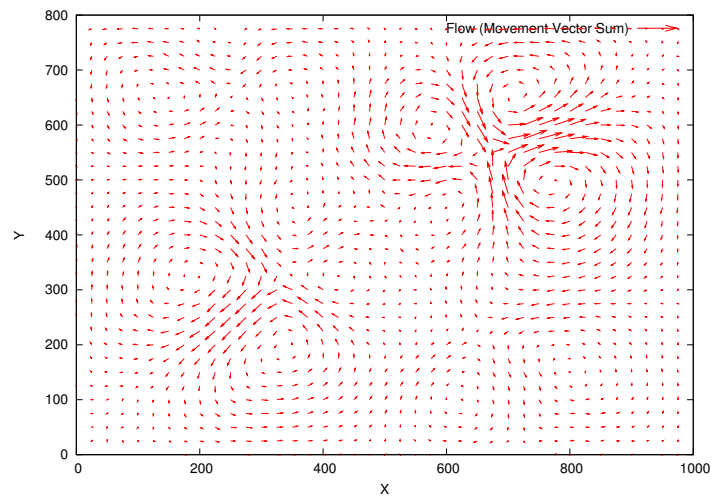
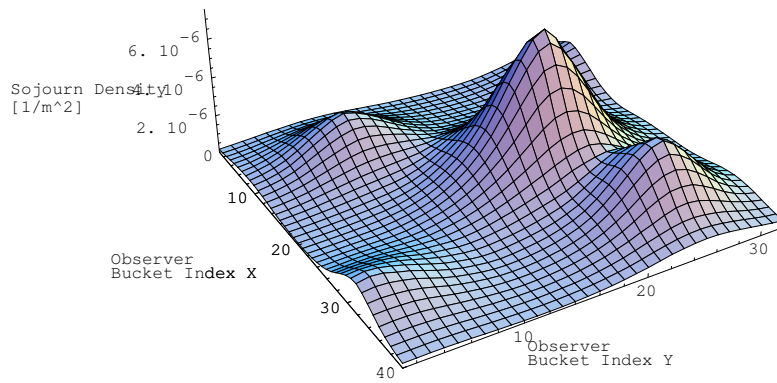
A second approach is to partition the simulation area into non-overlapping regions, as depicted in figure 3. Each of the resulting fields provides a set of distribution functions which are used to determine a next walk segment starting there. These distribution functions can either be closed form ones or empirically defined, i. e., by sampling points of a CDF. In section 4 will be shown that the latter approach is quite promising, as it allows to parametrize the model based on trace data. In principle, the shape of the regions can be arbitrary as long as they do not overlap and cover the whole walk area. For simplicity, we assume in the following that the walk area is subdivided into a grid with  $N$  columns and  $M$  rows, as depicted in figure 3.

Note that we assume that  $\varphi_i, l_i, v_i, t_{p,i}$  are independent and, thus, that the distributions are not correlated. With this walk model, the future evolution of a walker's state only depends on the current walker state, i. e., its position  $\vec{x}$ , when the walker is at a waypoint, or of the walk segment it currently walks on. Thus, the generation of new walk segments can be seen as embedded Markov process with the typical Markov properties like independence of how this state was reached, which can simplify analytical evaluations of this model.

## 3 Impact of Location Dependent Parametrization

### 3.1 Methodology and Metrics

For evaluating the mobility models, we use the metrics *sojourn density* and *movement vector sum*. There are many other metrics that could be considered as well, but the most important properties of a model can be analyzed with these metrics. The sojourn density is defined as the number of



List of mass points:

#	x [m]	y [m]	m [kg]
1	210.0	210.0	1000.0
2	510.0	510.0	1500.0
3	810.0	610.0	1000.0
4	780.0	50.0	1000.0
5	110.0	810.0	1000.0

Figure 2: Sojourn density plot (top) and movement vector field (middle) of a RD walker with gravity and 5 mass points (bottom). The walker mass is 80 kg.

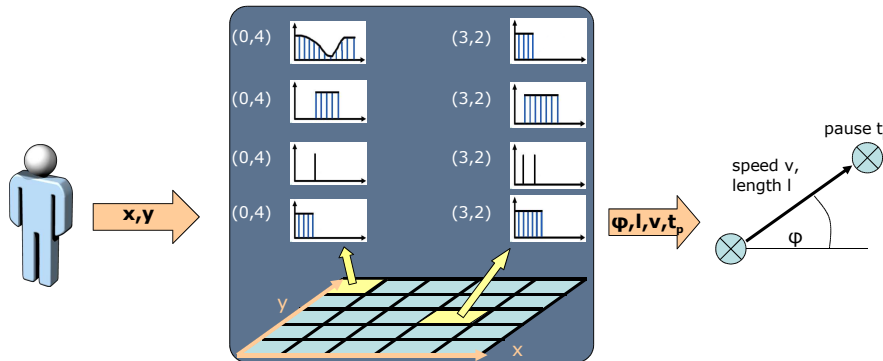


Figure 3: Grid of a random direction mobility model with location dependent parameterization

users  $n(t)$  per area  $A$ . The mean sojourn density is the average over the time and is thus given by

$$\bar{\rho} = \frac{1}{T} \int_{t_1}^{t_1+T} \frac{n(t)}{A} dt, \quad (6)$$

either as  $\lim_{t_1 \rightarrow -\infty, T \rightarrow \infty}$  or due to practical reasons for a sufficient large period of time  $T$ .

The movement vector sum is the vector summation of all moves  $\vec{v}(t)dt$  of users:

$$\bar{\phi} = \frac{1}{T} \int_{t_1}^{t_1+T} \frac{\vec{v}(t)}{A} dt. \quad (7)$$

In this metric, opposite directed moves nullify each other.

To explain the effects of location dependent parameterization, in the following two examples are presented. They visualize the impact of length and angle distribution choices on the sojourn density and the movement vector field. For the examples, a walk area of  $1000\text{m} \times 800\text{m}$  is taken. The local sojourn density and the movement is observed for small areas  $dA$  with a grid based observer with  $29 \times 24$  fields from  $(-80\text{m}, -80\text{m})$  to  $(1080\text{m}, 880\text{m})$ . For the RD-LDP parameterization, the walk area is subdivided into a grid of  $10 \times 8$  fields. Unless other mentioned, the angle distribution is uniform from  $0$  to  $2\pi$ , the speed is fixed to  $11\text{m/s}$ , the walk segment length is chosen uniformly distributed between  $0$  and  $30\text{m}$  and no pauses are configured.

The following studies are based on the IKR Simulation Library [12], a C++-library for event driven simulation tools, and an extension called MobiLib providing a framework for mobility related simulations and evaluations.

### 3.2 Effects of Changed Segment Length Distributions

The first example illustrates the effect that walk segment length distributions have on the sojourn density distribution of the walk area. For this, the segment length distributions of some fields tend to result in longer walk segments starting there. This increases the probability for these fields that walkers move far away and thus the sojourn density there diminishes. Figure 4 depicts the sojourn density distribution for uniform distributions from  $0$  to  $300\text{m}$  as standard, and uniform distributions from  $300\text{m}$  to  $400\text{m}$  as prolonged segment length distributions in the fields  $(4, 0)$  to  $(4, 4)$ . This graph shows very clearly the decrease of the sojourn density in the region of the fields with prolonged segment lengths.

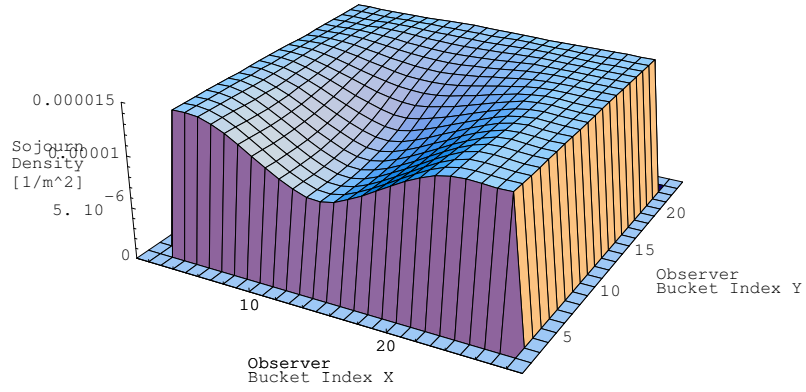


Figure 4: Sojourn density distribution of a RD-LDP walker with prolonged walk segment length distributions for the RD-LDP grid fields  $(4, 0) - (4, 4)$  of a  $10 \times 8$  grid

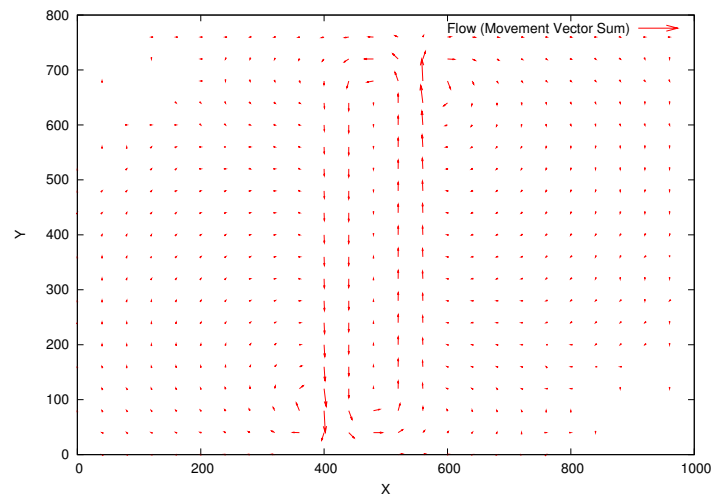
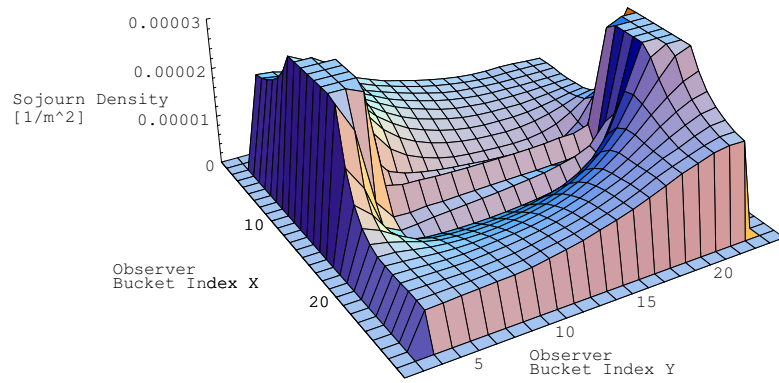


Figure 5: Sojourn density plot (top) and movement vector field (bottom) of a RD-LDP walker with two directed lanes at the fields  $(4, 1) - (4, 6)$  and  $(5, 1) - (5, 6)$  of a  $10 \times 8$  RD-LDP grid



### 3.3 Effects of Changed Angle Distributions

The second example visualizes the effects of the angle distributions to the sojourn density distribution and the movement vector field and shows a nice inhomogeneous scenario of a road with two lanes. For this, the angle distributions of the fields  $(4, 1) - (4, 6)$  produce values around  $3/2\pi$ , i.e. a uniform distribution covering the range  $252^\circ$  to  $288^\circ$  and the fields  $(5, 1) - (5, 6)$  having a uniform distribution generating values around  $\pi/2$ , i.e.  $72^\circ$  to  $108^\circ$ . Figure 5 shows the result of this scenario as sojourn density plot (left) and non-zero movement vector field (right).

### 3.4 Discussion

These two examples show that different scenarios can be configured with very little effort and without changing the movement pattern of point-to-point walks. This kind of modeling allows to create scenarios intuitively following qualitative rules. This especially applies for short walk length distributions since in this case the RD-LDP model has a fine control over walkers and since the influence of long walk segments passing several fields is small.

Analytical models to quantify the influence of the chosen distribution function to the walk area are challenging. Probably, a similar methodology like the one used in [7] for the RWP model could be applied here, too. However, since the distribution functions may be generic or even empirical, analytical evaluations are only of limited use and therefore left for further studies.

## 4 Automated Generation of Parameterizations

The RD-LDP mobility model allows to setup mobility scenarios in a very flexible way by appropriate distribution functions. While a manual setup of scenarios is possible, e.g. with a graphical editor as depicted in figure 6, we believe that a key advantage of the RD-LDP model is that the parameterization can be obtained automatically from existing mobility patterns like real-world traces. In this section, we introduce a method to transform existing mobility patterns to the RD-LDP model and we illustrate the feasibility of this approach for traces generated by the random waypoint mobility model.

### 4.1 Conversion Method

The RD-LDP model can be easily parameterized by a statistical analysis of existing traces, which can origin, e.g., from real-world measurements or from other mobility model simulators. In principle, any trace in form of a point-to-point walk can be used as input data. The parameterization of the RD-LDP mobility model requires three steps:

- Preprocessing: First, the trace data has to be fitted to the simulated walk area, typically a rectangle. This may require a clipping of the data. Also, the grid that defines the different configuration fields has to be chosen. As already mentioned, we use in this paper  $N \cdot M$  rectangles. The finer the granularity of the grid, the better the walkers can be influenced. But, of course, small grid sizes require more processing and storage. As shown in the next section, for pedestrian scenarios a grid length of the order of 100m may be an appropriate choice.
- Statistical analysis: By replaying the trace, the distributions of  $\varphi_i, l_i, v_i, t_{p,i}$  can be measured by observers within each field. The trace has to have enough data to obtain statistical valuable results, i.e. stable mean values.

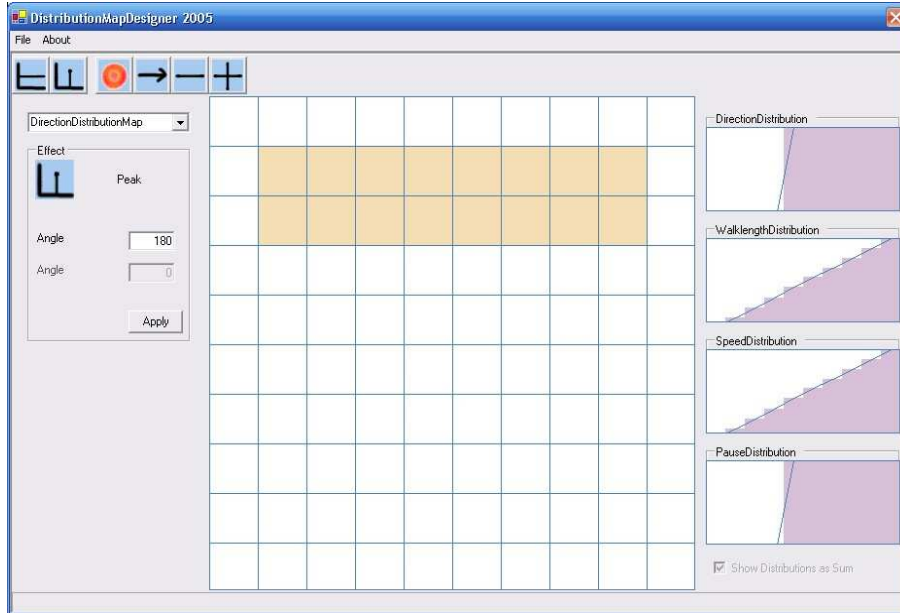


Figure 6: Graphical tool to edit 2D-arrays of empirical distributions

- **Parameter simplification:** The outcome of the observers in previous step are measured distribution functions. In order to simplify random variable evaluations in a simulation tool, the measurement results can be approximated by empirical distributions. The quality of this fitting depends on the number of sampling points, i. e., the number of used bucket  $K$ .

The resulting configuration of the RD-LDP model consists of  $4 \cdot N \cdot M$  distributions, each of them defined by  $K$  buckets.

## 4.2 Example: RWP to RD-LDP

Unfortunately, real-world traces that could be used as input for our model are hardly available to the public. We are currently involved in efforts to obtain fine-granular traces of pedestrians on a campus, which will allow to parameterize the RD-LDP model, but this data is not available so far. In order to demonstrate the feasibility of this parameterization, we use in the following traces generated by the RWP mobility model as example. In this case, the question is how well the non-homogeneous sojourn density of RWP can be modelled by RD-LDP.

Figure 7 shows the result of a comparison between the original RWP and the RD-LDP model, parameterized by the method described in the previous section. As metric we use the volume difference

$$e = \int_A \bar{\rho}_{RWP}(\vec{x}) - \bar{\rho}_{RD_LDP}(\vec{x}) dA \quad (8)$$

between the two sojourn density functions. The evaluation for various grid sizes  $N$  and distribution bucket numbers  $K$  shows that a quite small number of grid fields (e. g.,  $N = 4$ ) and buckets ( $K = 10$ ) is sufficient to achieve a quite good approximation.

## 4.3 Transforming Generic Mobility Traces

The method presented in section 4.1 can be applied to many different kinds of traces, as long as they contain sufficient data to obtain useful statistical values. Also, the original trace can be the

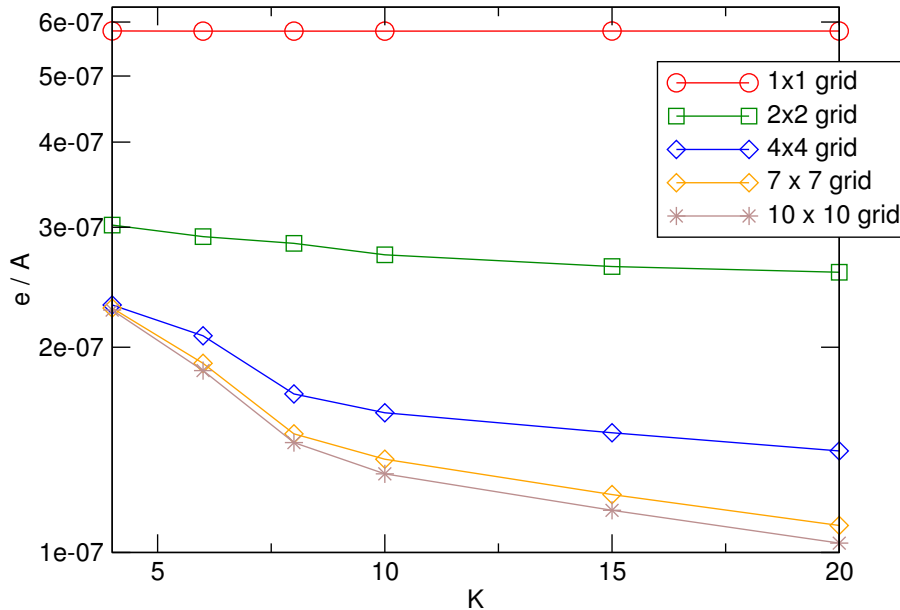


Figure 7: The normalized error between the original RWP sojourn density distribution and derived RD-LDP sojourn density distributions with different grades of effort for parameterizing the RD-LDP model. The effort for the RD-LDP parameterization is described by the grid size  $N \times N$  (here a quadratic grid is assumed) and the number  $K$  of buckets of the empirical distributions. The walk area size is used as normalization quotient.

observation of one single individual or a group of individuals as long as they have similar statistical properties. As result, the RD-LDP model provides a stationary, synthetic mobility model that is simpler to handle in simulation studies than the original traces.

However, it should be noted that our RD-LDP model does only approximate the original mobility characteristics, in particular if the grid is not very fine-granular, which is highly desirable for an efficient implementation in simulation tools. Due to the assumption that the random values  $\Phi$ ,  $L$ ,  $V$ , and  $T_p$  are statistical independent, some special mobility patterns cannot be reproduced correctly. For example, it is not possible to configure a field in such a way that short walks go to the left while long walks go to the right. A detailed study of the impact of this effect is still pending. However, we assume that this effect is not predominant in typical real-world traces and that the model can thus be parameterized very well.

## 5 Conclusions and Further Aspects

This paper shows that the location dependent parameterization of the random direction mobility model can be used to create inhomogeneous mobility scenarios in a very flexible way. In particular the proposed transformation of traces to RD-LDP parameterizations seems to be a promising approach to gain valuable realistic mobility models that meet the requirements of stationary simulation techniques. Besides this transformation of traces to RD-LDP parameterizations, scenario creation based on sojourn density or movement guidelines appears to be a valuable method for distinguished simulation studies with non-homogeneous mobility scenarios.

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