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Trace-based mobility modeling for multi-hop wireless networks

Nils Aschenbruck [a,*], Aarti Munjal [b], Tracy Camp [b]

[a] University of Bonn, Institute of Computer Science IV, Roemerstr. 164, 53117 Bonn, Germany
[b] Colorado School of Mines, Dept. of Math. and Computer Sciences, Golden, CO 80401, USA

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ABSTRACT

Realistic and scenario-dependent mobility modeling is crucial for the reliable performance evaluation of multi-hop networks. In the last decade, a significant number of synthetic mobility models have been proposed. However, only a few of these models have been validated by realistic movement traces. In the last few years, several of such traces have been collected, analyzed, and made available to the community. This paper provides a comprehensive and up-to-date survey of (1) available movement traces, (2) modeling/analyses of these traces, and (3) synthetic mobility models. The focus of the paper is on mobility traces/models that include position information. The contribution of this paper is to summarize the research that has been done in the area of mobility modeling over the last few years and present challenges for future work.

1. Introduction

Simulation and emulation are techniques frequently used for the performance evaluation of wireless networks. Compared to a testbed implementation, these techniques offer advantages concerning scalability, reproducibility, and cost-efficiency. Since the movement pattern of nodes is found to have significant impact on simulation and emulation results, it is required that mobility models emulate movements of nodes in a realistic way.

There are several mobility models available to date that attempt to capture the movement patterns of nodes in a realistic way. Synthetic mobility models are based on randomly generated movements and create synthetic traces. Unfortunately, simulation and emulation results of synthetic mobility models often do not match realistic scenarios. On the other hand, trace-based mobility models are based on traces captured from the real world. Because of their realistic nature, traces provide high accuracy in terms of movement patterns; however, they are difficult to model.

Synthetic mobility models have been used in the performance evaluation of various wireless network protocols; it is not surprising, however, that these models often fail to evaluate the protocols accurately. In order for the results obtained from a synthetic mobility model to be relied upon by the network community, it is highly desirable that the mobility model is validated by realistic traces. We note, however, that the analysis of such realistic traces can lead to different results depending upon the trace collection methods, size of the network population, and filtration techniques applied to traces (if any). Thus, results obtained by analysis of one trace may not be generalized to all the network scenarios. Nevertheless, trace-based modeling and trace-based validation are very important for credible performance evaluation.

Various synthetic mobility models have been proposed during the last decade. There have been several general mobility surveys [6,12,20,77,82] as well as a few specific surveys, e.g., for vehicular mobility models [33,37] and for tactical mobile networks [4]. To the best of our knowledge, however, there is no survey paper that provides a comprehensive and up-to-date survey of available traces, modeling/analyses of these traces, and synthetic mobility models. The contribution of this paper is twofold: (1) to summarize the work that has been done in the area of mobility modeling over the last few years (both synthetic mobility modeling and trace-based mobility modeling) and (2) to present challenges for future work.

The rest of the paper is structured as follows. Section 2 provides a survey on available traces and summarizes the results of recent trace-based analyses. We classify the traces based on scenarios and accuracy, in order to highlight the traces' ties to reality. Section 3 provides a comprehensive survey on synthetic mobility models, including their classification based on dependencies, applications/scenarios, and validation. In this context, we also survey mobility generators. In Section 4, we conclude with challenges for future research in the area of mobility modeling.

2. Traces

In this section, we (1) discuss the methods used to collect movement traces, (2) survey the traces that currently exist, and (3) present trace-based analyses for mobility modeling.

* Corresponding author. Tel.: +49 228 73 4117.
E-mail addresses: aschenbruck@cs.uni-bonn.de (N. Aschenbruck), amunjal@mines.edu (A. Munjal), tcamp@mines.edu (T. Camp).

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2.1. Acquiring traces

In principle, there are three methods to acquire traces. First, use a particular tool to monitor the location of the devices being traced. Second, monitor the communication of the devices to base stations of a communication system. Third, to monitor the contacts between mobile devices. We discuss these three methods to acquire traces in Sections 2.1.1, 2.1.2, 2.1.3, respectively.

2.1.1. Monitoring location

Currently, the Global Positioning System (GPS) is the most widely used outdoor localization system. It is based on satellites and provides location accuracy within a few meters when standard GPS receivers are used. The accuracy of a receiver's GPS location depends on the number of satellites the receiver can hear. There are specific tracking devices available that can maintain the device's GPS positions for a certain amount of time. Since GPS uses satellites, it is designed for outdoor environments only. Furthermore, if there are many buildings or other objects that produce shadowing effects (e.g., obstacles in urban areas or leaves on the trees in a forest), then the accuracy provided by GPS may not be sufficient.

One example of a localization system that works both outdoors and indoors is Place Lab [61]. With Place Lab, devices (such as laptops, PDAs, and cell phones) estimate their position by (1) listening for the cell IDs of fixed radio beacons (e.g., from wireless access points) and (2) referencing the beacons' positions in a cached database. A study in Seattle showed that 802.11 and GSM (Global System for Mobile communications) beacons are pervasive enough to obtain location accuracy of 20–30 m (median).

If more accurate positioning is needed, an RFID-based approach can be used. There are products (e.g., LPM[1], Local Position Measurement) available that promise sub-inch accuracy via an RFID-based approach. These systems, however, are quite expensive and need significant set-up time for calibration to obtain such location precision.

Kusy et al. [57] proposed another interesting approach, called Radio Interferometric Positioning (RIPS). In RIPS, a pair of nodes emit radio waves simultaneously at slightly different frequencies. A device can then estimate its position by using the relative phase offset of the signal measured from two receivers. An evaluation determined that RIPS offers location accuracy up to 3 cm. Alas, similar to LBM, RIPS is quite expensive and, similar to GPS, only works outdoors.

2.1.2. Monitoring communication

A second method to obtain mobility traces is to use existing communication systems and monitor the communication of the devices being traced. The location of a device can be approximated by monitoring the signal strength of the base station/access point (BS/AP) and/or the connectivity events of the device. If a device is connected to a cell (e.g., GSM) or an access point (e.g., WLAN), then the device makes the assumption that it is nearby the BS/AP. In addition, the device can monitor its signal strength and approximate the distance from the device to the BS/AP.

The accuracy of this communication monitoring approach is limited for two reasons. First, the accuracy depends on the density of the access points; in addition, if the density of the access points is quite high, a node may not be connected to the nearest access point. Second, this communication monitoring approach assumes that a strong correlation exists between a device's signal strength and its distance to the access point. This assumption is unlikely to hold, especially in environments where deep fading occurs. However, a communication monitoring approach is often used indoors as it is an inexpensive way to localize a node in a specific area (e.g., a room).

When a communication monitoring approach is used, the location trace data obtained may not be very precise (e.g., the location data only shows that the mobile device is within transmission range of some BS/AP). Nevertheless, one can use approximate location data to validate basic assumptions of microscopic mobility models. Furthermore, the accuracy of approximate data may be improved by applying methods of data fusion for tracking (e.g., [11]). The goal of data fusion is to associate, correlate, and combine information from a single or multiple sensors to achieve refined estimates. Bayesian-filter techniques (e.g., [30]), such as the Kalman and Particle filter, can also be used for retrodiction. These approaches are powerful and allow one to smooth the original trace data collected.

2.1.3. Monitoring contacts

A third approach to acquire traces is to use mobile devices that sniff for other mobile devices around them. By doing so, *contact traces* can be acquired. Contacts may be traced by using Bluetooth or WLAN in an infrastructureless mode. All other devices in range are seen as a contact. As the devices may be mobile these traces typically cannot be mapped on absolute locations.

For some kinds of networks, such as opportunistic networks (see, e.g., [84]), contacts between the mobile nodes may be more interesting than the actual position of the nodes. Furthermore, contact traces can be used to examine movement and social characteristics. Such characteristics can be used to develop new and validate existing models (e.g., [76]). Moreover, recently, there is ongoing work (such as [102]) to derive location-based traces from contact traces.

2.2. Available traces

In this section we provide a survey of traces that are currently available. There are several initiatives, CRAWDAD[2], UNC/FORTH[3], MobiLib[4] that provide repositories for real data traces. These repositories contain real traces from both realistic scenarios and testbed evaluations. The mobility pattern that exists in a trace from a testbed evaluation often depends on the evaluation done for that testbed (i.e., the devices do not move in natural patterns). For the validation of mobility models natural and realistic mobility patterns are needed. Thus, we do not discuss traces from testbed evaluations where the mobility of nodes is unique to the evaluation. In other words, for our survey, we focus on (1) traces from realistic scenarios and (2) traces from testbed evaluations where real-world mobility patterns occur.

We classify the traces according to the number of nodes used in the trace, the trace duration, the type of scenario, the data traced, and the repository where the trace can be obtained. We present our classification in Table 1. As shown, there are a lot of traces available. Many of these traces, however, are quite similar and only offer a limited number of different scenarios and applications. Specifically, Table 1 illustrates that the traces currently available are mainly for conference, campus, or city scenarios. Thus, one challenge for future work is to acquire accurate traces for different types of scenarios and applications.

In Table 1, we only list traces that are publically available. There are, of course, other traces that are not freely available to the community. Some of these (unavailable) traces have been used to generate synthetic traces (e.g., HWGUI[5]) and commercial simulators (e.g., VISSIM[6]). These simulators are often used by scientists from

[1] Abatec LPM – http://www.abatec-ag.com/.

[2] CRAWDAD http://crawdad.cs.dartmouth.edu/.

[3] UNC/FORTH http://netserver.ics.forth.gr/datatraces/.

[4] MobiLibhttp://nile.cise.ufl.edu/MobiLib/.

[5] HWGUI http://www.informatik.uni-mannheim.de/pi4/projects/hwgui/.

[6] VISSIM http://www.ptvag.com/software/transportation-planning-traffic-engineering/software-system-solutions/vissim/.

Table 1
Survey on available traces. Unless stated otherwise, *Nodes* refers to the unique users/MAC addresses in the traceset. (See below-mentioned references for further information)

Trace			Scenario	Traced Data					Repository		
Trace Source	Nodes	Trace Duration		GPS	GSM/UMTS Cell-ID	Connectivity (WLAN, Bluetooth, RFID)	Signal-Strength (WLAN, Bluetooth, RFID)	Contacts	CRAWDAD	UNC/FORTH	MobiLib
Dartmouth/Campus [34]	1000+	Apr. 11 '01 to Oct. 4 '06	Campus			√			√		
FORTH Campus	8 APs	Sept. '05	Campus			√	√			√	
MIT/Reality [25]	100	Jul. 26 '04 to May 5 '05	Campus		√	√			√		√
NCSU/NCSU [87]	3	Aug. 26 '06 - Nov. 16 '06	Campus	√					√		
NCSU/KAIST [87]	4	Sep. 26 '06 - Nov. 11 '06 Sep. 10 '07 - Okt. 03. '07	Campus	√					√		
Stanford/Gates [94]	74	Sep. 20 '99 to Dec. 12 '99	Office Build.			√			√		
UCSD [70]	275	Sep. 22 '02 to Dec. 8 '02	Campus			√			√		
UNC Campus [35]	14712	Sep. 29 '04 to Jun. 20 '05	Campus			√	√			√	
UPMC/Content [60]	40	Oct. 28 '05 to Dec. 21 '05	Campus/City			√			√		
USC/Mobilib [39]	4548	Apr. 19 '05 to Aug. 8 '05	Campus			√			√		√
IBM/Watson [9]	1366	Jul. 20 '02 to Aug. 18 '02	Office Build.			√	√		√		
HAGGLE/Intel [22]	128	Jan. 06 '05 to Jan. 11 '05	Office					√	√		
IleSansFil/Wifidog	45000	Aug. 28 '04 to Aug. 28 '07	City			√			√		
NCSU/NY [87]	8	Okt. 23 '06 - Nov. 24 '06 Dec. 18 '07 - Apr. 18. '08	City	√					√		
UW/Places [51]	3	Jun. 7 '04 to Jun. 10 '04	City			√	√		√		
HAGGLE/Cambridge [22]	223	Jan. 25 '05 to Jan. 31 '05	City					√	√		
HAGGLE/Content [22]	54 sensors	Oct. 28 '05 to Dec. 21 '05	City					√	√		
NOVAY/Cosphere [83]	11	Feb 1 '07 to Mar. 13 2007	City					√	√		
NUS/Bluetooth [78]	10,673	Feb 1 '07 to Mar. 13 2007	City					√	√		
EPFL/Mobility [85]	~500	Mai 17 '08 to Jun. 10 '08	Public Trans.	√					√		
Rice/ad_hoc_city [49]	1200	Oct. 30 '01 to Dec. 2 '01	Public Trans.						√		
UMass/Diesel [10]	40	Jan. 25 '05 to Dec. 14 '07	Public Trans.	√		√			√		
NCSU/Disney [87]	4	Nov. 19 '06 - Dec. 27 '06 Dec. 16 '07 - Jan. 09. '08	Scene-Park	√					√		
NCSU/NC-State-Fair [87]	8	Oct. 24 '06 Oct. 17 '07 - Oct. 21. '07	Fair	√					√		
UPMC/Rollernet [98]	1112	3h	Rollerblades					√	√		
HOPE/AMD	1281	Jul. 18 '08 to Jul. 20 '08	Conference			√	√		√		
Microsoft/OSDI2006	5 APs	Nov. 6 '06 to Nov. 7 '06	Conference			√	√		√		
UCSB/IETF2005 [48]	112 APs	Mar. 9 '05 to Mar. 10 '05	Conference			√			√		√
UCSD/Sigcomm2001 [8]	195	Aug. 29 '01 to Aug. 31 '01	Conference			√			√		
UW/Sigcomm2004 [88]	550	Aug. 30 '04 to Sep. 3 '04	Conference			√			√		
HAGGLE/Infocom05 [22]	274	Mar. 07 '05 to Mar. 10 '05	Conference					√	√		
HAGGLE/Infocom06 [22]	98 sensors	Apr. 24 '06 to Apr. 27 '06	Conference					√	√		
Nottingham/Cattle [103]	100	Jul. 4 '06 to Jul. 13 '06	Animal move.	√					√		
Princeton/Zebranet [65]	7	Jan. 12 '04 to Jun. 27 '05	Animal move.	√					√		

other domains (e.g., car manufacturers or city and road traffic planers). The models used in these domains are very *scenario specific* (e.g., city, urban, and vehicular scenarios) and usually very accurate. Thus, for some network performance evaluations (e.g., for vehicular networks) it makes sense to interlink simulators of different domains (see, e.g., [66]). By doing so, the domain specific models can be used to evaluate a communication system.

Many of the conference and campus traces listed in Table 1, such as [52], are acquired by measuring connectivity to WLAN access points. Unfortunately, as discussed in Section 2.1.2, the accuracy of this communication monitoring approach is limited. Since WLAN access points can only provide accuracy within WLAN range, the accuracy of the traces depends on the density of the access points. Furthermore, the connection of a device to one access point does not imply that this access point is the nearest one. For example, signal propagation in a building or between buildings is often specific to that environment.

One paper of note is [39]. In this work, the authors study and analyze traces from four different campus scenarios: MIT [9], Dartmouth [34], UCSD [70], and USC [39]. The authors discuss both the similarities and the differences of these four traces in detail. They found, for example, that while the traces are all campus scenarios, each of the traces used a different trace collection method and focused on different populations. One of the conclusions drawn by the authors from their analysis is that synthetic mobility models are not appropriate for modeling heterogeneous environments such as campus scenarios.

As discussed, one significant challenge for future work is to acquire accurate traces for many different types of scenarios and applications. There are many scenarios, e.g., disaster and battlefield scenarios, for which no traces are currently available. Furthermore, for some scenarios where traces are available, the accuracy of the traces is quite limited. Significant future work is needed to obtain accurate traces for different types of scenarios and applications. Ideally, the community should build a large base of detailed microscopic mobility models that are all validated through the collection of real-world trace data.

2.3. Trace-based analysis

Trace-based analysis offers new challenges not previously discussed. One challenge is the variation that exists in the trace data. This variation may be related to time (e.g., few people walk around a campus in the middle of the night) or day (e.g., no movement may exist in an office building on a weekend or a holiday). See [100] for an analysis of the variation that exists in a cellular trace for different days of the week. It is very important to consider these variations when doing trace-based analysis.

A second challenge is that it may be necessary to filter the data in the traces. For example, ping-pong effects between different WLAN access points were observed in [104]. In other words, since a building may have several access points available, a user may switch perpetually between two different access points without having moved in reality. One solution to this ping-pong effect is to aggregate data over different access points. While this solution will overcome all ping-pong effects in the data, the trace will loose location accuracy.

A third challenge in trace-based analysis is the need to acquire a sufficient number of samples to derive a mobility model. If the number of samples is too small, then the models developed may be biased by movement patterns that are specific to where the trace was acquired. For example, perhaps some students at Dartmouth College move differently than other students at University of Florida. One approach to overcome this challenge is to aggregate traces from several similar scenarios (e.g., aggregate the traces from Dartmouth and Florida). Of course, to aggregate traces, it is important that the parameters analyzed (e.g., metrics for speed and accuracy) in the traces fit together; otherwise, the traces will first need to be normalized. We note that this third challenge is also affected by the first two challenges. Specifically, when aggregating different traces, it is necessary to consider any variations that exist over time/day as well as any ping-pong effects.

In the following sections, we consider trace-based analyses and modeling for different scenarios. We first discuss human mobility in general including contact properties. We then discuss trace-based modeling of the following scenarios: campus, office, conference, and city.

2.3.1. Human mobility in general

GPS-traces of different scenarios (e.g., campus, metropolitan, fair) are analyzed in [87,59]. In their work, the authors discovered that pre-processing of the data was vital due to GPS errors indicating small changes in direction. For example, if one walks on a straight line, the pure GPS signal will jump back and forth on either side of the line. The authors reduced this noise by using different methods to aggregate short flight times (i.e., flights moving in the same direction) together.

The authors found several interesting features of human walks. First, human walks in these outdoor scenarios (within a scale of less than 10 km) show statistical resemblances to Levy walks. Levy walks are defined as random walk trajectories that are composed of self-similar jumps. Levy walks are more diffusive than Brownian motion, but less diffusive than movements following a random-waypoint movement pattern.

Second, the flight-times, the pause-times, and the inter-contact times of human mobility follow truncated power-law. This result is in line with [21] where power-law distributed inter-contact times where found by analyzing several contact traces. The authors of [59,87] determined that although the geographical constraints can vary in different scenarios, the power-law property observed is invariant. Thus, they conclude that human intentions and activities are scale-free and independent of geographical constraints. Third, humans do not move randomly over a simulation area. Instead, their mobility patterns are predefined and heterogeneous. Furthermore, popular locations to visit exist. Thus, locations visited can be modeled as Fractal Waypoints [69] and can be referred to as places visited by people with common interests.

2.3.2. Trace-based modeling of campus scenarios

The traces from campus scenarios are mainly connectivity traces, taken from campus wide WLAN networks. Table 2 provides an overview of the different analyses and models that have been developed from the campus traces available. Early analyses (e.g., [44,94,99]) show that users tend to spend most of their time connected to a small number of access points. In fact, [94] showed that users tend to spend most of their time at one location and short periods of time at a few other locations. In [99], the authors determined that the amount of time a user spends at a location follows power-law distribution with small exponents. In more recent work, i.e., [52], the authors refine that pause-times are lognormally distributed. We discuss pause-time distributions further in this section.

Using trace data from a campus scenario, a WLAN mobility model is proposed and validated in [99]. In this model, nodes move between different cells (access points) and the movement path is determined by transition probabilities between the cells. The parameters of this model are derived from and validated by the campus WLAN traces (see [99] for details).

The analyses of these campus scenario traces provide some interesting results and models; however, as we will discuss, the results and models from these campus WLAN traces do not contain all movements of a user; for example, in a campus scenario, a student may leave his/her WLAN device at the dormitory when the student moves to attend a lecture. In other words, the models developed from these campus WLAN traces have drawbacks when used in the performance evaluation of a communication system where the devices are ubiquitous and omnipresent.

VoIP phones and PDAs are more ubiquitous and omnipresent than laptops. Differences between the mobility patterns of laptops and VoIP phones mobility patterns have been seen (e.g., [34]). Thus, the statistical mobility model (i.e., [104]) was developed using trace data from *both* laptops and VoIP phones. To develop this statistical mobility model, the authors analyzed traces from both laptops and VoIP phones for transition probabilities and user densities. The authors discovered that the VoIP trace data was much more fine-grained than the laptop trace data. Since users are likely to keep a VoIP phone turned on at all times, the phone

Table 2
Different analyses and models that have been developed from campus data. See Table 1 for details on each trace listed. All models have been validated by the respective traces. (See below-mentioned references for further information)

Analysis / Model		Traces used						Devices used	
		Dartmouth/Campus [34]	ETH [99]	MIT/Reality [25]	Stanford/Gates [94]	UCSD [70]	USC/Mobilib [39]	Laptops	Phones / PDAs
Analysis Tang/Baker	[94]				√			√	
Analysis Jain et al.	[44]	√						√	
WLAN mob. model	[99]		√					√	
Analysis Henderson et al.	[34]	√						√	√
Campus waypoint model	[70]					√			√
WLAN mob. model	[52]	√							√
Statistical mob. model	[104]	√						√	√
Time-variant com. mob. model	[38,41]	√		√		√	√		√

registers with all the access points that it passes. Trace data for laptops, on the other hand, is more coarse-grained. To create synthetic fine-grained traces, the authors performed interpolation using topological information and simple heuristics. The movement pattern is then modeled as a second-order Markov chain that uses the movement probabilities between different map locations. The model is parametrized and validated by both statistical measurements (for laptops) and traces from devices (for VoIP phones).

Traces of PDAs are examined in detail in [70]. Similar to [104], the authors discovered that the users (students) are more mobile than the laptop traces would indicate. This result is not surprising, as a PDA (like a cell phone) is more likely to be carried by a user than a laptop. Using traces of PDAs, the authors of [70] propose the campus waypoint model. While this model is based on traces of PDAs, it works similar to the random-waypoint mobility model. The main difference is that locations, speeds, and directions in the campus waypoint model are actually based on traces of PDAs.

Both the statistical mobility model [104] and the campus waypoint model [70] provide trace-parametrized solutions to model a campus scenario at the building level. Neither approach, however, considers all of the challenges discussed in Section 2.3; specifically, neither mobility model developed considers any variations in the traces that exist over time/day nor location accuracy issues due to ping-pong effects.

As discussed in Section 2.1.2, the accuracy of the traces derived from monitoring the connectivity events of a device is limited. For example, the authors of [52] present significant differences that exist between the GPS-traces and traces based on a device's connectivity. While the devices (VoIP phones) are only monitored during the daytime hours in [52], the work illustrates that accuracy is a significant concern when only communication data is used for monitoring mobility. The authors of [68] second this concern. In [68], the authors present a testbed evaluation analyzing connectivity data in vehicular mobility. Their results illustrate that there is a complex picture of connectivity between base stations/access points and moving vehicles; specifically, they found that the passing of a vehicle through a base station's area is often marred by intermittent periods of very poor connectivity. Similarly, accuracy is a concern if mobility is determined by monitoring the signal strength of the base station/access point. For example, in [27], the authors evaluate the interference of the wireless LAN and conclude that inter-cell interference is common but not well-understood.

In order to improve the accuracy of connectivity traces, the authors of [52] perform retrodiction using a Kalman filter. The authors then propose a WLAN mobility model with the following features. First, nodes are classified as being either stationary nodes (when movement is less than 100 m in diameter) or mobile nodes. Second, stationary nodes are placed (and restricted to) hotspots (i.e., popular locations); mobile nodes, on the other hand, are allowed to start in any location within the simulation area. Third, mobile nodes choose a destination (a hotspot) to visit using a probabilistic transition matrix. Fourth, on the way to its chosen destination, a node visits several waypoints (intermediate locations). The waypoints are chosen within an area bounded by a box; the two diagonal end points of the box are the source and the destination. Lastly, due to data obtained from real traces, the pause-times and speed distributions are lognormally distributed. The WLAN mobility model presented in [52] is parametrized and validated by the traces.

The authors of [101] present a mobility model that combines mobile network traces presented in [52] with the weighted waypoint model presented in [40]. The model, called RealMobGen, is an easily available NS-2 mobility model for pedestrian movement on a campus scenario. Adopted characteristics from [52] include the direction of movement, speed distribution, initial location of nodes, pause-time distributions, ratio of mobile to stationary nodes, and start/stop time distributions for a node's active period. Adopted characteristics from [40] include details on hotspots, e.g., the time dependent probabilities of hotspot-to-hotspot transition decisions.

The authors of [41] present the time-variant community mobility model. The variance that exists in movement over time (see Section 2.3 for a discussion) is realized by modeling specific movement behavior for different time periods. Specifically, the model has local epochs and roaming epochs. During a local epoch, node movements are confined to the node's community (a local area). During a roaming epoch, the node is able to move anywhere in the simulation area. The transition between these two types of time periods is realized by a two-state Markov chain; thus, the time a node is in one epoch is distributed exponentially. To realize the time variance in the model, the transition probabilities of the Markov chain are varied for different time periods.

The authors of the time-variant community mobility model [41] show that their model can be parametrized to match characteristics of previously obtained WLAN traces. Furthermore, the same authors examined the behavior patterns of wireless users of different WLAN traces from different campuses and found that diverse communities exist [38,39]. This result fits previous results. Specifically, in [94], the authors found that users can be grouped into location-based sub-communities, each with its own movement, activity, and usage characteristics.

In conclusion, there has been intense research in the area of trace-based models for campus scenarios. Main results from the efforts thus far conclude that.

- users tend to visit popular places or hotspots,
- a user's movement is dependent on the user's community (e.g., his/her social network), and
- a user's movement will vary over time.

As discussed in this section, several different mobility models with characteristics of campus scenarios have been proposed, parametrized, and validated. The approaches and methodologies used for analysis and modeling of campus scenarios may, in principle, be used for other types of scenarios (e.g., city or disaster scenario). The main challenge is that few real traces exist from other scenarios.

2.3.3. Trace-based modeling of office scenarios

As shown in Table 1, very few traces for an office scenario exist. One trace that does exist is described in [9]. In this paper, the authors analyze movement traces from a corporate office building. The authors found that nodes spend long periods of time at one location; furthermore, when a node does visit another location, the length of the visit is for a much shorter period of time. The authors conclude that several characteristics found in their trace data matches characteristics found in other environments [53,94], specifically university campuses and public networks.

We note, however, that the trace data compared between the office scenario of [9] and other scenarios are from laptop devices only. As discussed in Section 2.3.2, differences exist between campus trace data of VoIP phones/PDAs and campus trace data of laptops; see [34,70] for details. Specifically, ubiquitous devices such as PDAs are much more mobile and visit several different locations on a campus. Thus, for microscopic mobility of ubiquitous devices, differences between campus and office scenarios may actually exist.

The authors of [72] analyze traces from a one-week sensor deployment in an office environment. The analysis focused on meeting locations of several people in an organization. Using the results, the authors then derive a meeting driven movement model. We note, however, that the amount of data obtained in [72] is much smaller than the amount of data obtained in [9].

In summary, very few traces exist for an office scenario and none of these traces use ubiquitous devices. One main challenge for future work is to obtain long-term traces of ubiquitous devices within office scenarios. Once obtained, researchers need to closely analyze the traces with the ultimate goal of developing an accurate office scenario mobility model.

2.3.4. Trace-based modeling of conference scenarios

In [8], a trace obtained at the 2001 ACM SIGCOMM conference is analyzed. Since only four access points were monitored during the conference, user location information was limited. Thus, the authors do not consider user mobility patterns in this work. Nevertheless, the authors did find a few interesting results. Specifically, the trace analysis showed that (1) the users were evenly distributed over the four access points and (2) the users were mobile when one would expect them to be mobile (e.g., at the beginning and end of a session).

Other traces of conference scenarios are available [8,88,47,48,46]. To the best of our knowledge, however, none of these traces have been analyzed in regards to mobility. Thus, similar to office scenarios, more work is needed to analyze traces from conference scenarios with the ultimate goal of developing an accurate conference scenario mobility model.

2.3.5. Trace-based modeling of city scenarios

A 1998 trace from a packet radio network is analyzed in [95]. The authors discovered that a large fraction of the users (65%) is only seen at one location per day. In addition, the more locations a user visits, the closer together those locations are.

In [89], the authors analyzed the movements of one user in Melbourne, Australia; the user movements were recorded daily in a logbook for 61 days. (Three of the 61 days had no movement.) The authors then proposed that a parametrized random-waypoint-like model could be used to model the movement of a user in a large city. The logbook results showed that pause-time could be modeled as a Chi-square distribution with degree of freedom equal to 0.5. In addition, the results showed that the path to the destinations must be modeled in a more complex way than the direct paths taken in the random-waypoint model. While these results are interesting, the trace is only from one individual and should not be generalized.

A few other traces of city scenarios are available (see Table 1). These traces have been measured in different contexts. There are papers available [10,49,51] in which the measurement architecture and the purpose of tracing are described; however, to the best of our knowledge, these traces have not yet been used for the analysis or modeling of mobility.

In conclusion, traces of movement within city scenarios need to be obtained and analyzed. Again, the ultimate goal is to develop an accurate city scenario mobility model.

3. Synthetic mobility models

In Section 2, we surveyed the traces that currently exist and presented trace-based analyses for mobility modeling. As discussed, the main challenge of synthetic mobility models is validation. One way (perhaps the best one) to validate a synthetic mobility model is to use traces collected from real-world movement.

In general, mobility models can be classified into three categories: microscopic, macroscopic, and mesoscopic mobility models. A microscopic model describes the movements of the individual nodes. Typically, location, velocity, and acceleration of the individual nodes are modeled over time in a microscopic model. A macroscopic model abstracts the individual movements and only models the parameters relevant to the system being evaluated. A typical example for a macroscopic model is the impact of the movement on a specific region (e.g., cell). In macroscopic models, abstract location and time-dependent metrics such as cell-change-rate or handover-traffic are considered. Mesoscopic models aggregate the movements of different nodes.

A microscopic model is appropriate when the movements of individual nodes have a decisive impact on the communication system. Recently, communication systems that contain multi-hop components, e.g., Mobile Ad-hoc NETworks (MANETs) or Mesh-Networks, are studied excessively. For the performance evaluation of these systems, microscopic models are needed. Macroscopic and mesoscopic mobility models are appropriate for different environments (e.g., cellular networks), and should not be used in the performance evaluation of wireless multi-hop networks. We, therefore, focus on microscopic mobility models in this paper.

Several microscopic mobility models have been proposed over the last few years. Some models have been developed for a specific scenario (e.g., disaster recovery), while other models have been developed to be more generic. The generic mobility models are typically easier to use than models that are scenario-specific, and often allow theoretical analysis. All existing mobility models can be classified according to the dependencies that exist within the model. An alternative classification is to consider the applications or scenarios for which the model was developed. In Table 3, we comprehensively classify the existing synthetic mobility models;

Table 3
Survey of existing synthetic mobility models. √ means the model has the dependency or belongs to the application/scenario or has been validated by traces measured in real scenarios; (√) means that the model somewhat has the dependency or somewhat belongs to the application/scenario, e.g., a subway does not represent a full city/urban scenario, or has been somewhat validated, such as by detailed scenario descriptions or expert interviews. (See below-mentioned references for further information)

Model		Dependencies			Applications / Scenarios						
		temporary	spatial	geographical	Campus	Pop Concert / Fair	City / Urban / Vehicular	Disaster Area	Battle-Field	Daily Movement	**Validated**
No dependencies											
Random-Waypoint	[50]										
Random-Direction	[90]										
Modified Random-Direction	[90]										
Random-Walk	[20]										
Random-Border-Model	[14]										
Random-Waypoint with attraction points	[14]					√					
Campus-Waypoint	[70]				√						
Random-Trip	[58]										
Clustered-Mobility	[64]		(√)					√			
Disaster-Recovery	[81]		(√)					√			
General Ripple	[23]										
Temporal dependencies											
Gauss-Markov	[62]	√									
Smooth-Random	[13]	√									
WLAN	[52]	√			√						√
Spatial dependencies											
Reference-Point-Group	[36]	(√)	√	(√)							
Structured-Group	[16]		√					(√)	(√)		
Virtual Track	[106]		√				√		√		
Social-Network-founded	[75]		√								
Mold	[63]		√		√						
Community-based	[76]		√								√
Home-cell Community-based	[17]		√								
Geographic Restrictions											
Manhattan-Grid	[28]			√			√				
Graph-based	[96]			√			√				
Obstacle	[45]			√	√						
Weighted-Waypoint	[40]			√	√						
RealMobGen	[101]			√	√						
Voronoi	[107]			√			√				
Area-Graph-based	[15]			√	√						
CosMos	[32]			√							
Hotspot	[67]			√		√					
Route	[67]			√			√				
Random-Waypoint-City	[54]			√			√				
Random-Street	[5]			√			√				
Agenda Based	[105]			√			√			√	
Statistical	[104]			√	√						√
Time-variant Community	[41]			√	√						√
Graph-Random-Waypoint	[73]			√			√				
Graph-Random-Walk	[73]			√			√				
Subway	[97]			√			(√)				

Table 3 (*continued*)

Model		Dependencies			Applications / Scenarios						Validated
		temporary	spatial	geographical	Campus	Pop Concert / Fair	City / Urban / Vehicular	Disaster Area	Battle-Field	Daily Movement	
Hybrid dependencies/restrictions											
Freeway	[7]	√	√	√			√				
Intelligent-Driver	[29]	√	√	√			√				
User-oriented-Meta-Model	[93]	√	√	√						√	
Meeting Driven	[72]	√	√	√			(√)				√
Street-Random-Waypoint	[24]	√	√	√			√				
VanetMobiSim	[33]	√	√	√			√				
SIMPS	[18]	√	√								
Hostage-Rescue	[43]		√	√					√		
Disaster-Area-Model	[3]		√	√				√			
CORPS	[42]		√	√				√			
Dispatched-Ambulance	[91]		√	√				√			√
Platoon	[86]		√	√					√		
TIMM	[2]		√	√					√		(√)
Working-Day-Model	[26]	√	√	√			√			√	
SWIM	[71]		√	√							
WLAN	[99]	√		√	√						√
SLAW	[59]	√	√		√	√	(√)			(√)	√

in this table, we consider both dependencies and applications/scenarios as criterion. In addition, we mark whether or not a model has been validated, or not.

Let us first consider dependencies of the existing synthetic mobility models. The microscopic models can be distinguished, analogous to [6], in the following three categories:

- *temporal dependencies*: the movement of a node is influenced by the node's movement in the past.
- *spatial dependencies*: the movement of a node is influenced by the surrounding nodes (e.g., group mobility).
- *geographic restrictions*: the movement of a node is restricted within some area defined for node movement.

There are some models, such as random-waypoint and random-walk, that do not exhibit any of these dependencies. More realistic models, on the other hand, are often scenario-specific and have one or more of these dependencies. Temporal dependencies are needed to model real world phenomena such as acceleration and deceleration. Spatial dependencies are essential to model community behaviors. Geographic restrictions, such as obstacles or streets, are everywhere and, therefore, also need to be considered.

In addition to the dependencies, we consider the scenario or application of the synthetic mobility models in Table 3. We classify the models according to the scenarios described in the respective papers: Campus, Pop Concert/Fair, City/Urban/Vehicular, Disaster Area, Battle-Field, and Daily Movement. Our classification of the models is based on what the authors of the models state in their papers. We note that a model created for one scenario may be re-parametrized to be applicable for another scenario.

As shown in Table 3, several models have been proposed for a given scenario or application. When a model is needed for a given scenario or application, it is very hard to decide which model to use, because of the large number of available models. If a model has not been validated, the model has not been shown to provide realistic synthetic traces. Thus, its value is limited. As shown in the table, most of the models have not been validated by realistic traces or any other measure. We regard the validation of existing synthetic models via traces as one of the biggest challenges for future research in the area of mobility modeling.

We note that there may be other classifications based on specific metrics for certain kinds of networks. One example for this is opportunistic networks. Opportunistic networks can cope with disconnections and perpetual network partitions. The nodes' mobility is seen as an opportunity to ferry data (see e.g., [84]). Thus, contacts between pairs of nodes and the distribution of inter contact times are of special interest for opportunistic networks. For this community it may be interesting to classify the models using their contact time and inter contact time distribution. Typically, exponential or power law distributions are expected (e.g., [21]). We cannot provide this classification in this paper as implementation for all models would be needed.

Furthermore, we do not provide details of the synthetic mobility models listed in Table 3; instead, we refer interested readers to the respective papers. Users of these models, however, are probably more interested in discovering the implementations of the models that are available. In Table 4 we present the available (free) tools that exist to generate several *synthetic* mobility traces; we do not list tools that are not publically available nor sites that only provide the implementation of one model. These sites are usually provided in the respective papers or can be easily found.

4. Conclusion and challenges for future research

Section 2.3 shows that several researchers have recently focused on analyzing traces. We note, however, that the accuracy

Table 4
Available tools for generating synthetic mobility traces. (?See below-mentioned references for further information)

Tool		Models
Toilers-Code-Base	[20]	Random-Waypoint (and steady-state variant), Random-Walk,
	[79,80]	Prob. Random-Walk, Random-Direction, Reference-Point-Group, Gauss-Markov, Column
`http://toilers.mines.edu/Public/CodeList`		
BonnMotion	[1]	Random-Waypoint, Gauss-Markov, Manhattan-Grid, Reference-Point-Group, Disaster Area
	[5]	Random-Street
`http://bonnmotion.net.cs.uni-bonn.de`		
Important	[7]	Random-Waypoint, Reference-Point-Group, Freeway, Manhattan-Grid
`http://nile.cise.ufl.edu/important/software.htm`		
MobiSim	[74]	Random-Waypoint, Random-Walk, Reference-Point-Group, Gauss-Markov, Freeway, Manhattan-Grid
`http://ce.sharif.edu/~sm_mousavi/mobisim.html`		
CanuMobiSim	[93]	Brownian-Motion, Random-Waypoint, User-oriented-Meta-Model
	[92]	Obstacles
VanetMobiSim	[29]	Intelligent-Driver
`http://vanet.eurecom.fr/`		
SUMO	[55]	Urban Vehicular Traffic
`http://sumo.sourceforge.net/`		

of these traces is often limited, mainly because most of the traces are from monitoring communication with WLAN access points. In addition, there is limited trace data and analyses for all scenarios except the campus scenario. Thus, much more work in this area is needed.

As shown in Table 3, several mobility models have been recently proposed; however, only a small number of these models have been validated by traces. As shown in Table 1, several traces from different measurements are available in repositories such as CRAWDAD, UNC/FORTH, and MobiLib. We encourage researchers to use these available traces and validate, or show failure of, the models proposed in Table 3.

As discussed throughout this paper, there is a huge demand in this area for future work. We encourage researchers to use the analyses, approaches, and methodologies of previous work as a basis for future research. In the following list, we highlight several key challenges for future research in the area of realistic mobility modeling:

- The development of positioning and trace acquisition systems of sufficient accuracy (see Section 2.1) is necessary for capturing representative traces. New powerful devices (e.g., smartphones) offer the opportunity for collecting more accurate traces; when using these devices, privacy issues may arise that have to be considered.
- The acquisition of representative traces of all kinds of scenarios (see Section 2.2) is needed for a trace-based validation and model development. For some scenarios, e.g., disaster area and battlefield scenarios, there are no traces available. For other scenarios, many available traces do not have the level of accuracy needed for detailed modeling and validation.
- The evolution of general approaches that overcome the challenges of trace-based analysis (see Section 2.3) is important for all trace-based analyses. General approaches are needed (1) to deal with the variation that exists over time, (2) to filter ping-pong effects (e.g., access point associations), and (3) to allow comparability, normalization, and aggregation of different traces.
- If one is able to obtain representative traces of non-campus scenarios, then substantial analysis for these scenarios is needed. In this context, existing models should be parametrized and validated.
- The traces available can be used for interdisciplinary research as well. They may be used for exploiting social behavior as well as understanding cultural and country-specific differences. Based on this, new models can be developed.

Further challenges for future research can be found in [31].

One interesting avenue of research that has not been discussed herein concerns the modeling of application driven movement. In this case, the distributed application may have an impact on the movement of a node. For example, consider UAV Group Reconnaissance Applications (e.g., [56]) or discovery of available parking places in vehicular networks (e.g., [19]).

In closing, when developing a mobility model as accurate as possible, a researcher should keep in mind the use of the model. A performance analyst (who does not do research in mobility modeling) prefers simple and easy-to-use models. Thus, a more detailed (and, therefore, more complex) model makes sense *only if* the included details have an impact on the results of a performance evaluation with the model. If there is no impact on the results of a performance evaluation, then there is little use for a more detailed model.

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