



## Human Mobility Model for Theme park Visitors in Wireless Networks

### KEYWORDS

Mobility model, human mobility, mobile wireless network ,theme park

### P.Sheela Rani

Assistant Professor, Dept of Information Technology, Panimalar Institute of Technology, Anna University, Chennai, India

### S.Shamili

IIIrd year Student ,Dept of Information Technology, Panimalar Institute of Technology, Anna University, Chennai, India

### R.Sumitha

IIIrd year Student ,Dept of Information Technology, Panimalar Institute of Technology, Anna University, Chennai, India

**ABSTRACT** Realistic human quality modeling is essential for correct performance analysis of mobile wireless networks. Movements of holiday makers in theme parks have an effect on the performance of systems that square measure designed for numerous functions together with urban sensing and crowd management. antecedently projected human quality models square measure principally generic whereas a number of them concentrate on daily movements of individuals in urban areas. Theme parks, however, have distinctive characteristics in terms of terribly restricted use of vehicles, crowd's social behavior, and attractions. Human quality is powerfully tied to the locations of attractions and is synchronic with major diversion events. Hence, realistic human quality models should be developed with the particular state of affairs in mind. In this paper, we tend to gift a unique model for human quality in theme parks. In our model, the non-determinism of movement selections of holiday makers is combined with settled behavior of attractions in a very pleasure ground. The realism of the model is evaluated through intensive simulations and compared with the quality models coleslaw, RWP and also the GPS traces of pleasure ground guests

### Introduction

Recent advances in mobile devices enabled the increased popularity and usage of mobile applications. Urban sensing applications, wherever largely good phones area unit used, and wireless device networks with mobile sinks area unit examples of these applications. The realistic modeling of human movement has important importance for the performance assessment of such mobile wireless systems. Human quality models simulate the movement patterns of the mobile users and that they kind a key component of the simulation-based performance analysis one in all the foremost necessary characteristics of human quality is that the combination of regularity and naturalness when deciding consequent destination. The current human quality models will be classified into 2 teams as trace-based and artificial models. The trace-based models typically use GPS traces and Bluetooth connectivity observations. However, it's troublesome to collect real information and also quantity of publically accessible data is restricted. Therefore, artificial models, that area unit defined on mathematical basis, area unit wide employed in simulations. Most quality models aim for a generic human movement modeling. In an amusement park, on the opposite hand, the movement would be determined by the attractions planned to be visited.

Theme parks area unit giant thronged areas with distinctive characteristics in terms of movement patterns of tourists, attractions in varied locations and walking methods connecting the attractions. The outputs of the model area unit the synthetic movement tracks, pausing locations (waiting points) and pausing times. First, the shape points area unit generated by the model so as to form the pausing locations. These locations area unit grouped into four main attraction varieties of theme parks: main rides, medium-sized rides, live shows, and restaurants. The waiting times of tourists at these attractions area unit sculptures using queueing theory. Moreover, we tend to outline walking area unit as of visitors as landmarks within the pleasure

ground so as to separate the walking methods from the roads on that transportation vehicles are being employed.

Let us currently contemplate however such a model is beneficial for wireless mobile applications. as an example, a wireless sensor network (WSN) will be deployed in a very pleasure ground for finding the quickest thanks to move from one location to a different considering the present density of the crowds in numerous areas of the park. Another category of applications would be the theme park administration.

During this paper, we tend to gift a quality model of theme park visitors considering the nondeterministic macro-mobility decisions of the guests also because the settled behaviors of the attractions. The outcomes of the planned model area unit synthetically generated mobility traces. These quality traces area unit compared to the real-life pleasure ground GPS traces and also the traces of two mobility models.

### Human mobility model

In this section, we present the scenario-specific mobility model for the theme park visitors. Theme parks are large areas with one or more "themed" landmarks that consist of attractions. Visitors of a landmark plan to see a subset of these attractions by walking during their scheduled visit. SLAW model provides an effective strategy in representing social contexts of common gathering places of walking people by fractal points and heavy-tail flights on top of these fractal points. We use this idea as a baseline for a more model and apply queueing models to represent the behavior and effects of different types of attractions on mobility of theme park visitors.

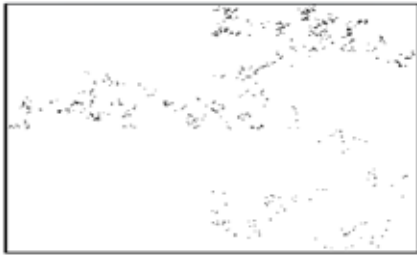
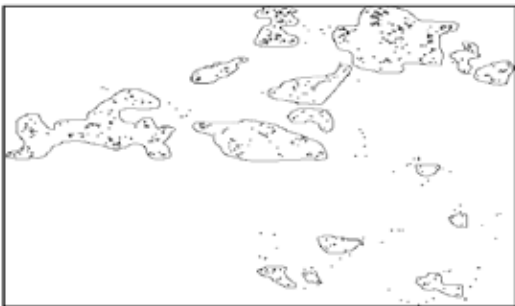


Fig. 1. Fractal point generation phase of the model.

**Modeling a theme park  
Clusters**

After generation of the fractal points, we determine the parts of the area with highest density of the points. The goal of this phase is finding the popular areas, where people are more attracted to gather together. We use a modified version of DBScan algorithm on the generated fractal points to find the attraction locations. DBScan is a density based clustering algorithm for discovering clusters with noise points, which has two input parameters, epsilon Eps and minimum number of points MinPts. In our DBScan approach, for each point in a cluster, there are at least MinPts neighbors in the Eps-neighborhood of that point. Let us assume a landmark is required to have 10 clusters and the proportion of non-clustered points to be approximately 0.10. The initial epsilon and minimum number of neighbors are set as 30 meters and 8 empirically. After setting the initial values, the fractal points are scanned iteratively to set the new values for epsilon and number of neighbors parameters. When the expected number of attractions and the expected approximate proportion of non-clustered points are achieved, the clustering of fractal points are finalized.



Clusters generated by DBScan over 1000 fractal points.

**Landmarks**

Landmarks are generated as a result of the previous steps ,including the generation of fractal points, density-based iterative clustering, generation of queues according to their weights, queue types, and service rates. In this phase, we form landmarks by addition of visitors, which are mobile elements of a landmark. A specified number of visitors are distributed to attractions and noise points randomly. The random distribution is done according to the weights of attractions, and the weights of the noise points are set to 1. A landmark is a place where there are multiple static queues, static noise points and mobile visitors. Each landmark has two dimensions specifying its size.

**Funfair Map**

For modeling the funfair, we tend to use a graph theoretical approach. The funfair map is shaped as a graph consisting of vertices and weighted non-directional edges. Each vertex within the graph represents a landmark. If

there is a road between 2 landmarks, a foothold is added with a weight which cherishes the transportation time. Theme parks area unit typically massive areas with transportation services among the most locations of attractions such as buses, trains and cars. By separating landmarks as vertices in an exceedingly funfair graph model and adding weighted non-directional edges between the landmarks, we tend to generalize the model of human quality in a landmark to the human mobility within the whole theme park. we tend to do not assume that a subject park may be a uniform 2nd space, since it includes geographical obstacles like areas without pavements for pedestrians and methods or roads used for transportation. These characteristics change our mobility model to be a lot of realistic compared to the prevailing models.

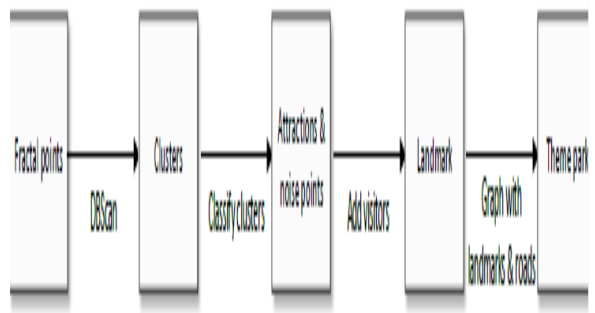


Fig 2 The phases of modeling a theme park

Fig 2 illustrates the phases of our model in a step by-step fashion. These phases start with the generation of fractal points, density-based clustering and continues with the generation of attractions and the noise points. Attractions, noise points and visitors all together form a landmark shown in the fourth phase. In the last phase, multiple landmarks and roads are modeled with a graph.

**Visitor model**

In the model, the visitors are represented by mobile nodes. We outline the states of the mobile nodes in an exceedingly landmark as "initial", "in Queue", "moving", "inNoisePoint" and "removed". At the start of the simulation, all mobile nodes are in "initial" state. A mobile node changes its state to "inQueue" once it starts waiting in an exceedingly queue. The state changes to "in Noise Point" once the node starts waiting in a noise purpose. There are 2 different states of waiting in order to differentiate waiting in an exceedingly queue.

**Algorithm to find the next destination**

```

For each n in N
do
Pr(n)=(1/d(cp,n)α
End for
For each α in A do
Pr (a) =(1/d(cp,n)α
Pr(a)=Pr(a)*W(a)
End for
    
```

```

Select a point p based on the probabilities Pr from the
set N
If p∈N then
Return Position of the noise point p
Else
Return Position of a random point in the queue p
    
```

End if

At each iteration of the simulation, we check the queues to find the number of visitors serviced and the states of all visitors for possible changes. For instance, if a visitor is serviced by an attraction, the state of the visitor must change from "inQueue" to "moving". When an attraction is selected, the visitor goes to a random sit-point inside the clustered area as the new destination position. Waiting time of a visitor in a queue depends on the number of visitors already waiting in the queue ahead of that visitor, service rate and the number of visitors per service of the attraction. When a visitor goes to a noise point, the waiting time of the visitor is generated using the truncated Pareto distribution.

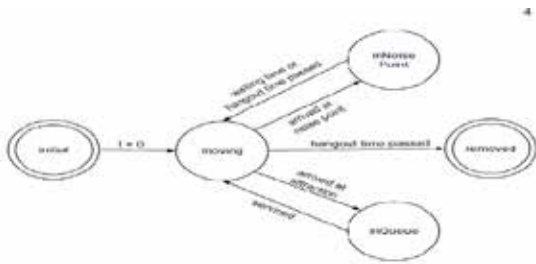


Fig 3 states of a visitor

**Pleasure ground with multiple landmarks**

Assume an oversized pleasure ground consisting of 3 main parks as shown in Fig. 4. During this figure, landmarks are the vertices and therefore the lines connecting landmarks are the perimeters with totally different weights. Open Street Map is used as an instance the model on this map. As you will see, the parks have labels L1, L2 and L3, and the weights of the perimeters between them have labels W1, W2 and W3. The landmarks will be generated in keeping with the particular sizes of the areas of the most parks, and therefore the weights are set with the particular transportation times. Dimension and numbers of attractions are set for every park.



Fig 4 An illustration of model to a real-world scenario: Disney world parks in Orlando

**Simulation study**

**Simulation environment and metrics**

In this section, the experiments area unit administrated to valid ate our quality model in landmarks and observe the consequences of the distinctive parameters of the model.. Mobile nodes within the simulation draw their trajectory lines whereas moving. These mechanical phenomenon lines area unit the consecutive points within the figure, that illustrate the movement of the mobile nodes within the landmark.

**Simulation Results**

We conducted simulation experiments and generated synthetic mobility traces of the theme park (TP) mobility

model. The mobility traces are analyzed by comparison with 41 GPS traces from the CRAWDAD archive, which are collected from smart phones of 11 volunteers who spent their holidays in the Walt Disney World parks. The average duration of the mobility traces is approximately 9 hours with a minimum of 2.2 hours and maximum of 14.3 hours. The GPS tracking logs have a sampling time of 30 seconds. We examine fundamental characteristics of mobility features, including distribution of flight lengths, average flight lengths, distribution of waiting times and waiting rate of the mobile nodes For SLAW and RWP, equally sized areas are used for the comparison with our model. For the GPS traces, we assume that a visitor is not walking if the visitor moves for more than 150m in 30 seconds sampling time, which would exceed the average speed of a person.

Accordingly, the data is filtered for the time when the visitors are not walking, but possibly traveling with a bus or another vehicle in the theme park. Although publicly available GPS traces are limited and only 41 traces were used, the traces include mobility data for approximately 400 hours in the theme park. For the number of waiting points per hour results, approximately 400 outputs are analyzed. Each of the other GPS traces results are based on minimum 4000 outputs.

**3.2.1 Flight lengths**

A flight length is the distance between two consecutive waiting points of a visitor. A waiting point is defined by an attraction or a noise point. In this experiment, we compared flight length distribution of the TP mobility model with GPS traces, SLAW and RWP mobility models. The flight length distribution of the GPS traces represents the mobility decision patterns of the real theme park visitors.

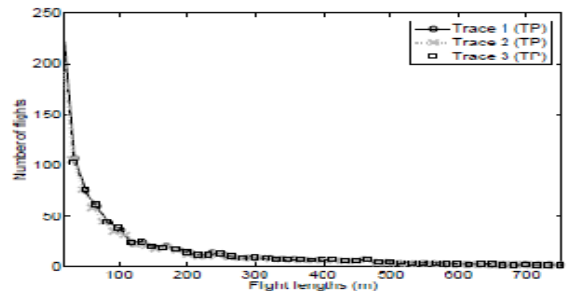


Fig 5 Flight length distributions of different traces of TP

**Number of waiting points**

In this experiment, we analyzed the number of waiting points averaged for one hour for the 3 models and the GPS SLAW and RWP for 5 trace sets. Average number of waiting points of GPS traces is approximately 10.5, which means every visitor is waiting at roughly 10 different locations in an hour on average. The figure shows that TP model performs significantly better than SLAW and RWP in terms of waiting rates of the mobile nodes. In Fig. 7, the number of waiting points will be increased if the number of attractions increased since the attractions become closer to each other, the flight lengths will be reduced. Fig.8 includes the results for noise point ratios ranging from 0% to 25%. The noise point ratio has a significant impact on the number of waiting points. As the ratio increases from 10% to 25%, the mean value of the number of waiting points increases approximately by 50%.

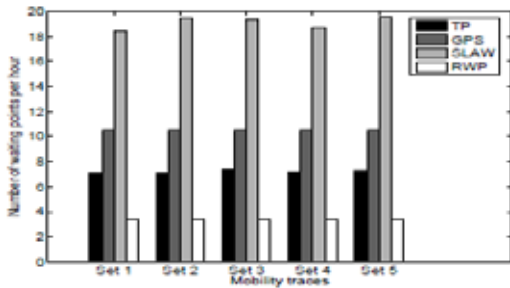


Fig 6 Number of waiting points per hour for TP, GPS, SLAW, RWP for 5 trace sets

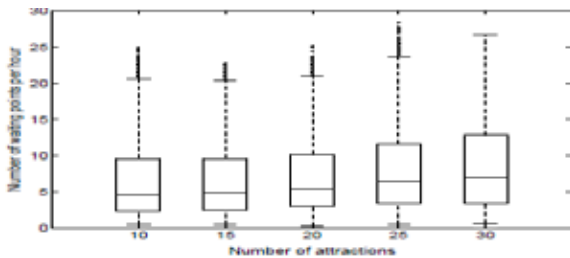


Fig 7 Number of waiting points per hour for TP with 10,15,20,25 and 30 attractions

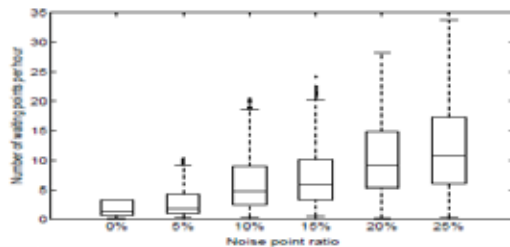


Fig 8 Number of waiting points per hour for TP with different noise point ratios

**Conclusion**

In this paper, we tend to be stowed a model for the movement of visitors during a theme park. In this model, we be apt to combined the nondeterministic behavior of the human walking pattern with the settled behavior of attractions during a theme park. We incline to divided the attractions into teams of main rides medium-sized rides, live shows and restaurants. we tend to used queuing-theoretic models to calculate times spent by visitors at totally different attractions. We valid accuracy of our model through in depth simulations mistreatment theme parks, GPS traces collected during a real funfair and also the knowledge generated by simulations of alternative quality models. The results show that our model provides a much better match to the real-world knowledge compared to salad and RWP models. We believe that a very important outcome of our work is that the generation of realistic quality traces of funfair guests for theme parks with numerous scales. The techniques developed during this paper will be accustomed model human quality in places that restrain individuals from mistreatment transportation vehicles. While networks with human participants have become more and more widespread, there is still a necessity for more analysis in human quality models.

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