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Analyzing Mobility Models

by

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MASTER OF SCIENCE

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Abstract

Mobility model is a hot topic in many areas, for example, protocol evaluation, network performance analysis and so on. How to simulate human mobility is the problem we should consider if we want to build an accurate mobility model. Therefore, the characteristics of human mobility will first be analyzed in this thesis. Our conclusion is that there are 6 main characteristics which can represent human mobility, these characteristics are pause time; return time, velocity and acceleration, direction angle change, displacement, radius of preferred area. With this conclusion, we compare the performance of current mobility models with those characteristics. Then our new mobility model is introduced. The results show us that this new model has better performance in several aspects, to be specific, 5 characteristics of human mobility except direction angle change. It means this model can be regarded as an accurate and realistic mobility model. None of the existing mobility models can reach this accomplishment. At the end, we will discuss about how we can improve this mobility model in the future. That could be an instruction for research in next stage.

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Table of Contents

1   Introduction

Human mobility has been widely studied in many areas like urban planning, traffic forecasting and avoiding the spread of biological and mobile viruses[1],[8]. It's also an essential topic used to improve the performance of wireless ad-hoc network. For example, protocols can be designed based on the regularity of nodes movement pattern. As the mobile devices are often carried by human, it's important to study the human mobility in order to simulate the MANETs in a more accurate and realistic way. Recent research has proved that human movement is not random but regular.[8] Furthermore, it has been indicated that despite the regularity of individuals, the human mobility has some generic performance.[4]

The results of previous studies [1]-[9] are useful for analyzing human movement pattern and are therefore being used to predict human trajectory. Nevertheless, all these studies focus on partial characters of movement pattern; none of them present an overall discussion of all characters. So, first we will have a comprehensive study of all the characters of human mobility, considering the factors that can impact human movement pattern. Then a more accurate and generic mobility model can be designed in the future.

Although the daily human behavior is complicate, there are still some common facts that could be used to represent human movement pattern. In this thesis, we discuss various characters of human mobility according to the previous papers [1]-[9]:

1. Pause time; 2. Return time; 3. Velocity & Acceleration; 4. Direction angle change; 5. Displacement (Flight length); 6. Preferred Area & Boundary

The combination of these characters can present the human movement pattern perfectly.

Then we discuss the existing mobility models in chapter 3, analyze that which characters have been considered in each model and which characters have been missed or represented in an unrealistic way. This part can be used to evaluate the performance of mobility models and to find the relation between these characters

and models. We will also talk about the impact of physical, psychological and environmental factors on human mobility. These factors can be recognized as the reason that caused the regularity and differences of human movement pattern, and also can be used as prerequisites which should be considered before model construction.

According to all these results, we considered preferred area as a foundation of human mobility and mobility model. Based on that, a new model is designed and evaluated in this thesis.

1.1   Importance of mobility model

Recently, with the deployment of all kinds of wireless devices, wireless communication is becoming more important. In this research area, Ad-Hoc network is a hot topic which has attracted much of research attentions.

A wireless ad hoc network is a decentralized wireless network. The network is ad hoc because it does not rely on a preexisting infrastructure, such as routers in wired networks or access points in managed (infrastructure) wireless networks. Instead, each node participates in routing by forwarding data for other nodes, and so the determination of which nodes forward data is made dynamically based on the network connectivity [31]. There are different kinds of routing protocol defined by how messages are sent from the source node to the destination node.

Based on this, it's reasonable to consider node mobility as an essential topic of ad-hoc network. With an accurate mobility model which represents nodes movement, designers can evaluate performance of protocols, predict user distribution, plan network resources allocation and so on. It can also be used in healthcare or traffic control area.

Since the mobile nodes are either attached to or controlled by humans, a mobility model that aims to represent nodes mobility equals a model that represents human mobility. In that case, the performance of a mobility model can be evaluated according to the characteristics of human mobility.

Currently, there are many existing mobility models, for example, random walk mobility model, random waypoint mobility model, random direction mobility model and self-similar least action walk model. The detail analysis of these models will be discussed later, but the basic situation is that none of them can fit all the characteristics that we extracted from human mobility.

1.2 Existing mobility models

As discussed in the previous paragraph, many mobility models have been proposed. We will discuss them thoroughly in Section 3. To start with, here we only introduce some of them.

- Random Walk mobility model

  Random walk model (RWM) model aims to simulate the unpredictable movement of entities in nature. In RWM, each node chooses speed and direction uniformly from pre-defined ranges $[V_{\min}, V_{\max}]$ and $[0, 2\pi]$, respectively. With the chosen speed and direction, a node moves for a constant time interval Δt or a constant distance Δd, and then arrives at a location, then remains stable for a predefined pause time. After that it starts to move again, following the same rule. There are two kinds of RWM [13]: either assuming a constant travel time Δt or a constant travel distance Δd, If a node moves to the border, its direction is reflected by the border and the same speed is maintained.

- Random Waypoint mobility model

  In Random waypoint mobility model (RWPM), a MN (mobile node) begins by staying in one location for a certain period of time (i.e. pause time). Once this time expires, the MN chooses a random position in the simulation area as the destination, and a speed that is uniformly distributed between minimum speed and maximum speed assigned. The MN then travels towards a new destination at the selected speed. Upon arrival, the MN pauses for a specified time period before starting the process again. [13]

3

As we will discuss disadvantages of RWP model in chapter 3, clustering of nodes occurs near the center of the simulation area because MN tends to select center area as destination or pass through it. But a fairly constant number of neighbors per node are necessary throughout the simulation [14]. Random Direction Mobility Model is therefore designed to overcome this problem.

- Random Direction mobility model

  To alleviate the clustering behavior and promote a semi-constant neighbors number, the Random Direction Mobility Model let the MNs choose a random direction, rather than random position, in which to travel similar to the Random Walk Mobility Model. An MN then travels to the border of the simulation area in that direction. Once the simulation boundary is reached, the MN pauses for a specified time, randomly chooses another angular direction (between 0 and 180 degrees) and continues the process [13].

- Self-similar Least Action Walk model

  Compared to the previous 3 models which can only represent the random movement, mobility model SLAW introduced by paper [22] is a more accurate and realistic model to represent human mobility. Every day, the user selects some compulsory visit points from the points that have already been distributed in whole simulation area. Then he adds some selective visit points to his destination list, after that, he will plan the path and move along it. At each position, he will pause for a pause time randomly selected from power-law distribution function. Detailed information will be explained in chapter 3.

These mobility models are examples, which based on them we realize that the mobility model is a hot topic in mobile network. They also remind us that the disadvantages of them cannot be ignored. According to our research, there are 6 main characteristics of human mobility, and none of these existing mobility models can represent them all. The best one is SLAW, which has realistic performances in 3 characteristics.

The details will be discussed in chapter 2, after we analyzed the 6 main characteristics of human mobility.

1.3 Goals of the Thesis

The aim of this thesis is to build a new mobility model which can simulate human movement in an accurate way. The main goals of this thesis are as follows:

1. Study the characteristics of human mobility
2. Analyze the disadvantages of existing mobility models
3. Determine the objective of the new model and design it accordingly
4. Add more characteristics of human mobility than other models
5. Implement the proposed model
6. Analyze the performance with simulation

1.4 Structure of the Thesis

First, the motivation and background information of mobility model is introduced, Then characteristics of human mobility are summarized. Afterwards, existing traditional mobility models are analyzed. Then we introduce and implement a new mobility model. The performance of this model is evaluated and compared to the main characteristics of human mobility. The remainder of this thesis is organized as follows:

Chapter 2 gives a survey of the performance of human mobility. Firstly, the properties of human mobility are discussed. Six main characteristics of human mobility are analyzed. Then we present various mobility models, evaluate their performance and discuss their advantages and disadvantages. Finally, we summarize the limitations of these mobility models and provide the aspects that need to be focused on in the new mobility model design.

In Chapter 3, the proposed new mobility model is presented. We provide a mobility model with a special aspect as foundation; the invisible boundary performance

exists in human mobility. Then we consider the idea that nodes distribution and visit points' distribution both have self-similar performance. By using these 2 basic rules, we can generate a realistic mobility model step by step.

Chapter 4 offers explanations of various experiments and simulation results, which include the performance analysis between the results of new mobility model and characteristics of human mobility. The simulation results show that our mobility model works well in various situations.

Chapter 5 summaries this thesis by giving a conclusion, which includes the contributions of our mobility model. Moreover, the limitations of our work and the future works are presented.

2   Human Mobility

As we have explained in previous chapter, to build an accurate mobility model, the first thing we need to do is to evaluate the real traces of human movement. By analyzing the performance of human mobility, we can therefore abstract several characteristics which should be considered as the main aspects of human mobility.

Because of the difficulties in getting real data by ourselves, we can evaluate the human mobility performance by analyzing the results according to other papers.

2.1   Objectives of human mobility model

Since mobility model is a model which can represent mobile users' movement accurately, we should evaluate users' mobility, which is equal to human mobility, and use the characteristics of human mobility as our model's objective.

2.2   Characteristics of human mobility

In this section, we will first analyze the time related characteristics of human mobility. As a start, we consider the pause time first, which means the time human stay in a place continually, and then we turn to the return time which indicates the time needed before the human revisit the place.

The spatial performance is the representation of human trajectory. The shape of trace, the way how human can arrive at the destination, and the active area of human daily life are all displayed by spatial performance. The three items of spatial performance are direction angle change, displacement (also named as flight length) and preferred area& boundary. All these previous characters have real data support in existing research papers.

At the end of this section, we will also mention about 2 more characteristics that have not been analyzed before, the travel time and regularity of human movement.

2.2.1 Pause time

In [1], the Complementary Cumulative Distribution Function (CCDF) of pause-time distribution is listed. The pause-time has almost no relationship with the velocity or displacement, which is reasonable because pause-time means how long the human "stay", not "moving". But it doesn't mean pause-time is a useless component for human mobility research.

We can see from the Figure 2-1 of [1] that the pause-time distribution changes for different scenarios. The sample settings where traces are obtained are two university campuses (KAIST in Asia and NSCU in the US), one metropolitan area (New York city--NYC), one State fair (SF) and one theme park (Disney World--DW). To specify the abbreviation, KAIST shows the data got from an Asia university campus, and the NSCU from US. In all the scenarios, except State fair, curves fit with truncated power-law distribution [1]. However, a short-tail distribution fits the pause-time CCDF in State fair. It's because state fair has many small shops and game arcades close to each other, the participators tend to make many short stops. Furthermore, the traffic setting also prevents them from staying at one location for a long period.
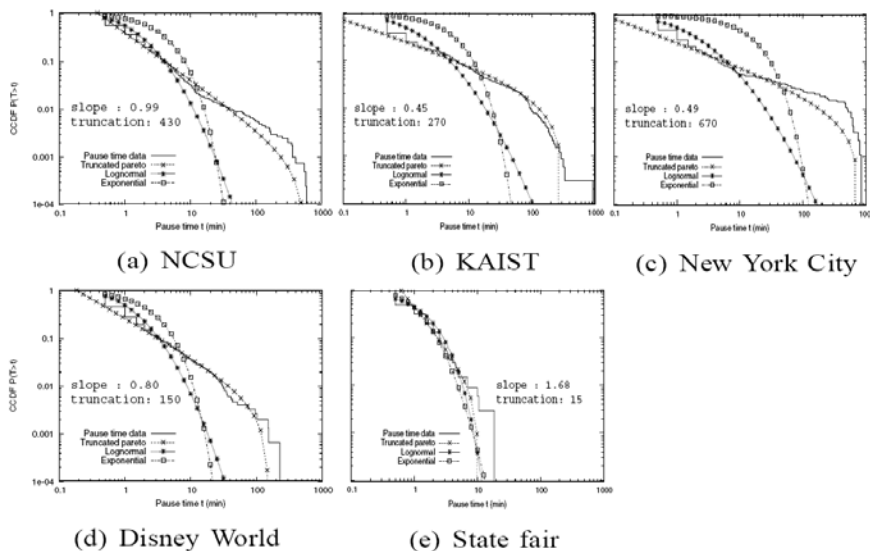

Figure 2- 1 The pause time's CCDF of human walkers in various scenarios along with the curve of various known distributions.[1]

In [5], the result is that the pause time also follows a power law distribution. There is a significant inflexion point which has been defined as "characteristic time" existing in the CCDF of pause time, before this characteristic time, the curve follows power law distribution and leads to a sub-diffusive human movement pattern, beyond it the curve changes to exponential distribution.

In [3], pause-time has also been discussed. But the result is different. The author claims that the pause-time of human fits lognormal distribution according to minimum MSE (mean square error) estimation method and most of participators don't pause at all. The mean value of pause time is 3.6 seconds, which is the only data provided for this distribution in [3]. After the analysis, we find that the different opinion in this paper is caused by the different experiment period and scenario. The author records the trace data in a park and the longest time of traces is only 1300 seconds. This dataset can only be used to study the short period performance of human walk; it's not enough for pause-time evaluation.

In [6], impact of pause-time has been discussed a little. When the researchers use adjacency and reachability to evaluate the connectivity of a student network, they compare the original data with the dataset without pause-time. Adjacency means the number of peers that a node can contact directly. Reachability means the number of peers that a node can contact either directly or indirectly. The result is that the reachability of a student network remains high even though the class time has been removed from the curve; on the other hand, the loss of adjacency is more obvious.

From these papers, we can say that the pause time of human mobility is in accordance with power-law distribution, the measurement happens in some special scenario should be considered as an exception, i.e. short measurement period and small area like a park.

Since the pause time shows us how long human stays inside a place, for the next characteristic we will discuss the return time, which indicates the time that a human is outside a place.

2.2.2 Return time

Humans are expected to return to certain location, like home or office/school. The strong tendency of human returns to particular place within a time period introduces the characteristic named return time. Return time can be used to prove the regularity of human mobility therefore to predict the location of human beings in application.

In [5], first they define return time: A return time of a device to a set of a space is defined as the minimum time until the device enters the set, from a time instance at which the device exited the set [7]. Then the researchers consider the CCDF of aggregated return time to a common site and find out that power law distribution also dominates the return time of human mobility. The interesting thing is, similar to our observation of a characteristic time on the CCDF of pause time, they have found an inflection point on the "power law - exponential" curve, the point is named as characteristic time.

In [8], they measure the return probability for each individual *Fpt(t)* (first passage time), defined as the probability that a user returns to the position where he/she was first observed after *t* hours. They find that the return probability is characterized by several peaks at 24 h, 48 h and 72 h, capture a strong tendency for human to return to the locations they've visited before, describe the recurrence and temporal periodicity inherent to human mobility.

Basically, the return time has 2 features, power-law distribution and the periodic regularity of returning to the start point every 24 hours. Pause time and return time both belong to the temporal performance of human mobility.

2.2.3 Velocity and Acceleration

The parameter we evaluate after the temporal performance is velocity and acceleration of human mobility. They can be considered as a connection between the temporal performance and the spatial performance. In particular time interval, the higher velocity human has, the longer distance he can move.

The Figure 2-2 below can give us a first impression of human movement velocity performance in Disney World. The speed of human mobility has high correlation with flight lengths: velocity increases as flight lengths increase. [1][2]

However, to understand this characteristic, we first need to introduce the definition of flight.

A flight is defined to be the longest straight line trip from one location to another that a mobile user makes without any directional change or pause [2]. In [1], three methods which are used to reduce the noise and error are described to extract flight from real traces and exclude noise. They are rectangular model, angle model and pause-time model. The detailed information of these models will not be specified here, however, the basic idea of abstracting flight is combining the fragments line together unless a long period pause or a sharp turn happened. Figure 2-2 shows us the velocity distribution over the flight length which is extracted by using these models from dataset of Disney World.
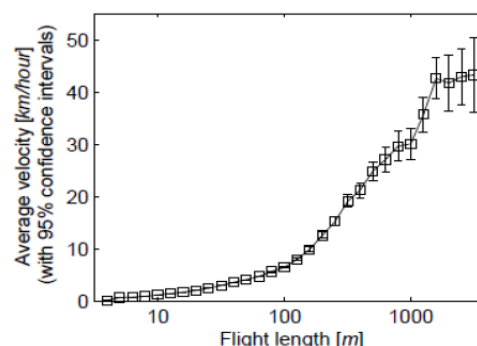

Figure 2- 2 Relation between velocity and flight length in Disney World[2]

In [3], the distribution of velocity has also been discussed. Figure 2-3 shows the epdf of human velocity in a park, which actually is not adequate for generic analysis because it only contains the data of human walk without any consideration of vehicle. We can see from this graph that the human walk velocity can be estimated as normal distribution. The start part of this curve has a different shape from normal distribution because the GPS they used can't actually record the pause accurately, instead of recording velocity as 0, it records minor positive values. Therefore, a

large amount of captured smaller values instead zero leads to this concentration. [3]
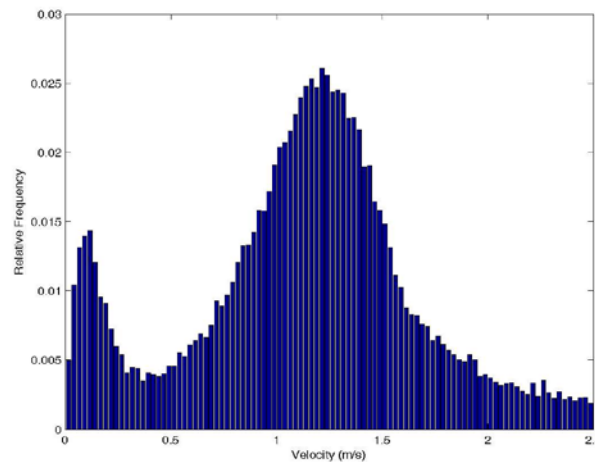

Figure 2- 3 Empirical probability distribution function (epdf) of velocity component

In the same paper [3], acceleration of human walk, which can be used as representation of velocity variation, has also been studied. The result is that acceleration also fits Normal distribution. However, this can't be used as a genetic result either. The change of scenario or environment will result in variability of velocity and acceleration performance, which will be discussed more in section 2.2.5.

2.2.4 Direction angle change

After we finished the discussion about velocity and acceleration, we can now move on to the evaluation of spatial performance of human mobility. The first characteristic in this part is the direction angle change during human movement.
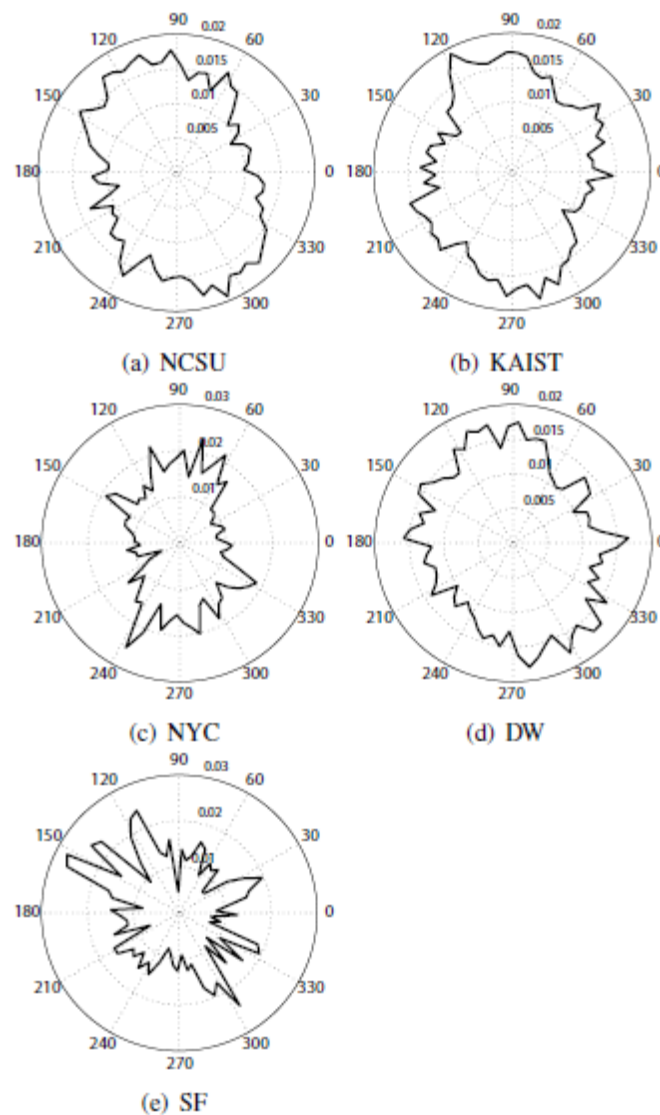
Fig. 13. Direction distribution from human walk traces.

Figure 2- 4. Direction distribution from human walk traces[4]

Figure 2-4 from [4] shows the turning angle distributions from all traces they recorded in 5 scenarios. The research group uses mobility track logs obtained from 44 participants carrying GPS receivers from September 2006 to January 2007. The angle distribution represents the effect of the geographical constraints.

We can find that while the turning angles recorded by most scenarios produce uniform distributions, the New York City traces have more bias in particular directions like 90 and 270 degrees. This pattern is related to geographical artifacts that the city roads tend to induce more perpendicular directional changes.[1][2][4]

This phenomenon is easier to be noticed in another paper [25], the turning angles exhibit a very sharply peaked bimodal distribution. In this paper, the data was acquired by recording the traces of taxis. From the difference between these 2 papers, [4] and [25], it's easy to realize that the performance of direction angle change depends particularly on the using of vehicles. Figure 2-4 is messier than Figure 2-5 because the traces of human walk are included in the dataset of Figure 2-4.
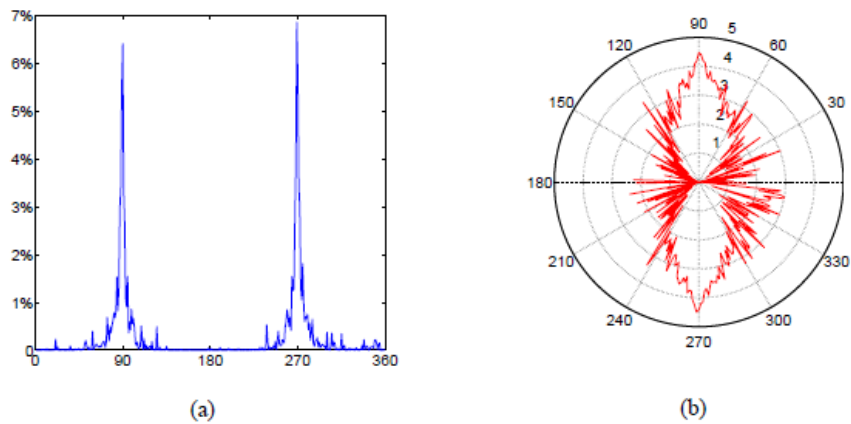

Figure 2- 5 Distribution of the turning angle with the flights.（a） Histogram in the range of 0–360 degree.（b）The same histogram in a polar plot with logarithm for the frequency. [25]

From [5], the author defines trips as separated only if there is either a gap or pause time more than 3 minutes between two consecutive timestamps of the trace dataset. Draw a straight line from the start to the end, the length of this segment is named as the trip displacement. The mobile users tend to decide a direction at the initial point of whole trip, have a strong "memory" of it and prefer to move along a straight line if possible. However, with the increasing of trip displacement, the trip direction changes more frequently. That means the longer trip of human is deeper impacted by the geographical constraints.

In [3], unlike the sharp turn behavior of the RWP model, the human movement presents a smooth variation in direction angle change. This can be seen in the direction angle change distribution of real movement obtained from the experiments

in [3], in which we can find that most of the angle values are smaller than 45 degrees, however, the direction angle change of RWP model is uniformly distributed between 0 and 180°.

The difference between [3] and [4] can also be used as a support of the result in [5]——a short trip tends to be straight but a long trip tends to be zigzag. In [3], the trip displacement is quite short because the data is recorded in a small area. But in [4], data was recorded in New York City, Disney World and so on. The conclusion is that the long trip displacement caused the frequently direction change. To push this conclusion further, we will discuss the displacement as the next characteristic.

2.2.5 Flight length (Displacement)

In [8], by measuring the distance between user's positions at consecutive calls, the researchers find the distribution of displacements over all users is well approximated by a truncated power-law distribution:

$$P(\Delta r) = (\Delta r + \Delta r_0)^{-\beta} \exp(-\Delta r / \kappa) \qquad \text{Equation 2- 1}$$

In this equation, [8] provides some constant values according to their research: exponent $\beta = 1.75 \pm 0.15$; $\Delta r_0 = 1.5km$ and cutoff value κ changes according to different scenarios.

It suggests that human motion follows a truncated Levy flight, the same result as [1].

In [5], the author defined the inflexion on the displacement CCDF as "characteristic distance" which is important to evaluate human mobility. It turns out that there is a "power law – exponential" dichotomy in the CCDF of trip displacement (Figure 2-6). There always is a characteristic distance, before which the CCDF has a power law decay, and beyond which it drops exponentially.

The probability density function of flight length is estimated as $f(l) \sim \dfrac{1}{l^{1+\beta}}$, in which the power law coefficient $\beta = 0.31$ (slope in Figure 2-6).

The mobility of students in a campus is recorded. And the result shows us, the curve has a "characteristic distance" which is the same order as the campus side length. There exists an "invisible" boundary of human movement in this scenario. Up to this "characteristic distance", trip displacement of participators follows power law distribution, upon that point, exponential distribution take the place.
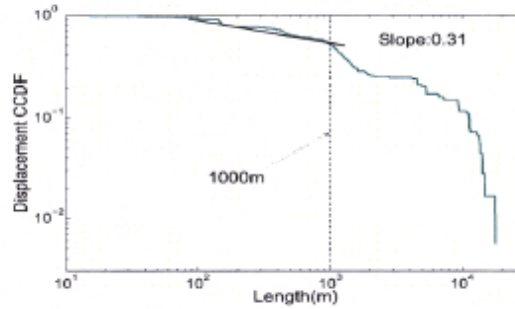

Figure 2- 6 Aggregated trip displacement CCDF[5]

All of these analyses direct to the same fact, the displacement of human mobility follows the power law-exponential dichotomy. Further than a particular distance, the human mobility is limited. This limitation leads to the emerging of next topic-- boundary of human activity.

2.2.6 Preferred Area and Boundary

In [5], trip displacement has the property of "power law-exponential" dichotomy. Beyond the characteristic distance, the distribution of displacement fits exponential distribution.(Figure 2- 6)

Also in [8], an inflexion point also exists in the curve of displacement distribution.

The parameter r_g is the radius of preferred area defined in detail in the supplement material of [8]. Calculating the radius of gyration r_g for all users, this paper shows us the distribution of r_g also can be approximated with a truncated power-law distribution. The difference of r_g has a strong impact on the truncated Levy behavior seen in the distribution of displacements. A sudden change always happens

16

when the displacement is in the same order as r_g. To be specific, this means the individual trajectories are bounded beyond r_g. Large displacements, which are the source of the distinct and anomalous nature of Levy flights, are statistically absent. Before the inflection point, the distribution of displacement can be seen as power law distribution. Beyond it, exponential displacement shows again.

Compare paper [5] to [8]. In [5] (Figure 2-6), the characteristic distance is proportional to the side length of campus, which can be treated as the "preferred area" in [8].

The similarity between these 2 papers is not coincidence; we can find the relation between [5] and [8]. Paper [8] defined an "invisible" virtual boundary of campus-associated territory. But combining with the result in [5], we believe that there is a boundary not only in campus environment but also in all human beings' daily life.

This characteristic also relates to the time interval during which the researchers record the human mobility data. For example, if a person needs to go abroad 3 months for vocation, in this time interval, the preferred area of that person is different from his normal preferred area.

2.2.7 Travel time and Regularity

After the introduction of all those characteristics that have already been studied before, there are still several characteristics that have not been discussed yet.

One of them is travel time. If we assume that the velocity and direction can be considered as constants, then the travel time can be easily calculated by dividing the displacement by the velocity.

However, the real scenario is much more complicate than previous assumption. The reason which makes travel time a valuable characteristic is that the estimation of travel time before the trip started is one of the most important characteristic for deciding the travel pattern. The research shows that if the travel time is longer than a threshold, human tends to change his travel pattern, i.e. if the distance is too long

and the human needs to walk several hours to get the destination, then he will choose cars or bus in most of the cases. The choice of vehicle is the essential condition of human mobility, which will be explained more in section 3.1.

Another characteristic which hasn't been analyzed before is the regularity of human mobility. Indeed, most of the papers have talked about the existence of the regularity in human daily traces, and used it as a basic assumption of human mobility research. But none of them have analyzed the percentage of daily trace overlapping. How exactly the trajectory of a man today equal to the trajectory of him in yesterday? How did they define the regularity? Show up in the same place at the same time? If a man walks on the particular roads everyday but on different time period, then how can we define the regularity of his movement? 100% or 0%?

The accuracy of this characteristic can impact the usage of mobility model or prediction method. A detail analysis with accurate data and clear definition is in need.

2.3   Analysis of existing mobility models

To achieve better performance for a mobility model, first we need to know what the disadvantages are of currently existing mobility models. Find the weak point of them from our analysis, use it as a break through point to build the new model, that is our goal of this section.

Using the real data of human mobility, we can therefore evaluate the performance of mobility models. Mobility model can be used to evaluate the performance of protocols for mobile ad hoc networks. The movements of mobile nodes are generated by selected mobility model, which means the accuracy of mobility model is vital to evaluate a new protocol successfully. However, there are many mobility models have been designed till now but none of them is perfect. As we can know, every mobility model has presented some of the characteristics we introduced in section 2.2. But the performance of mobility model is mostly different from the real trajectory. In every subsection, we will first define the model, and then talk about the advantage and disadvantage of this model.

2.3.1 Random Walk Mobility Model

The emerging of RW model aims to simulate the unpredictable movement of entities in nature. The definition of this model has been introduced in section 1.2.

This model addresses direction, velocity, and travel time characteristics in an inaccuracy way.

Pause time fits a uniform distribution between 0 and maximum time assigned.

Return time can only be evaluated if it's a 1- dimension or 2- dimension lattice random walk. But on an infinite 3- dimension grid, nodes are not guaranteed to return to where they start.

Velocity and direction of RW model fits uniform distribution.

As for the displacement of 2 kinds of random walk models in section 1.2, the RW model with constant t has a same displacement distribution as its velocity. The model with constant d has constant displacement.

When we consider the preferred area of random walk, we can find that take a random walk until it hits a circle of radius r times the step length. The average number of steps it performs is r^2. In two dimensions, the average number of points the same random walk has on the boundary of its trajectory is $r^{4/3}$. [23] The most directly way to know how the nodes in a random walk model are distributed is to check the Figure 2-7 we use here.

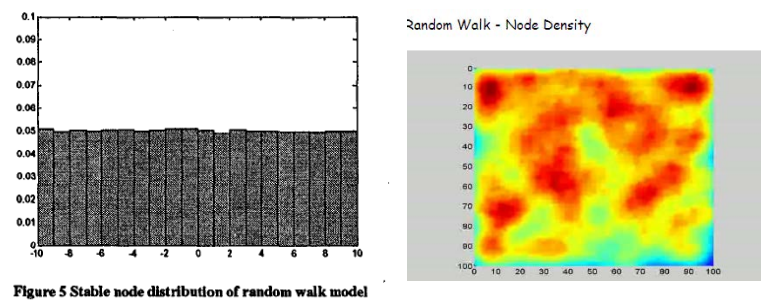Figure 5 Stable node distribution of random walk model

Figure 2- 7 Spatial node distribution of RW model. (Left: Node transaction density of RW model. [20]   Right: Visible node distribution of RW model)

Consider the performance of random walk model; we can say it is unrealistic due to its memoryless character. Sudden stops or sharp turns which are not common phenomena in human mobility can be generated in this model [13].

2.3.2   Random Waypoint Mobility Model

This model defined in section 1.2 can present the displacement, velocity and pause time of human mobility.

Pause time is a predefined constant. Velocity of nodes shows a trend of decrease with the increasing of simulation time.

To solve the problem of average speed decay, there are 2 methods can be considered:

1. Reduce the range of selected speed.

2. Discard the first period of simulation data to warm up.

The direction of nodes' movement has been discussed in [24]. The distribution of movement direction is decided by the starting point. If the node first starts from the central of simulation area, the direction fits a uniform distribution. Otherwise, node locates at the border of the area.

Now we can think about the distribution of RWP's displacement.

From [24], in RWP model, the average displacement of nodes in a square area is the longest. For the simulation areas with the same surface, the displacement tends to be shorter if the simulation area is long and narrow.

There is also some particular performance of node distribution in RWP model, for example, after a period of simulation time, node density in the center area is the highest of whole simulation area.

From these performance evaluations, although the RWP model is commonly used, it still has several problems.

The most important one is that RWP's zigzag movement pattern is different from the trace in real world, which will impact the accuracy of MANETs simulation.

Another disadvantage is the clustering of nodes occurs near the center of the simulation area, MN tends to select center area as destination or pass through it.

The reason for this inhomogeneous distribution is obvious in [20]: In order to set the direction of a node, the random waypoint model chooses a uniformly distributed destination point rather than a uniformly distributed angle. Therefore, nodes located at the border of the simulation area are very likely to move back toward the middle of the area or choose a destination point that requires the node to pass the middle of simulation area.

2.3.3   Random Direction Mobility Model

As we have discussed in the disadvantages analysis of RWP model, clustering of nodes occurs near the center of the simulation area. But a fairly constant number of neighbors per node are necessary throughout the simulation. [14] Random Direction Mobility Model was designed to overcome this problem.

To alleviate the clustering behavior and promote a semi-constant neighbors number, the Random Direction Mobility Model let the MNs choose a random direction, rather than random position, in which to travel similar to the Random Walk Mobility Model. An MN then travels to the border of the simulation area in that direction. Once the simulation boundary is reached, the MN pauses for a specified time, randomly chooses another angular direction (between 0 and 180 degree) and continues the process. [13]

In RD model, as we can see from the Figure 2-8, the density of nodes is higher on the simulation area's boundary.
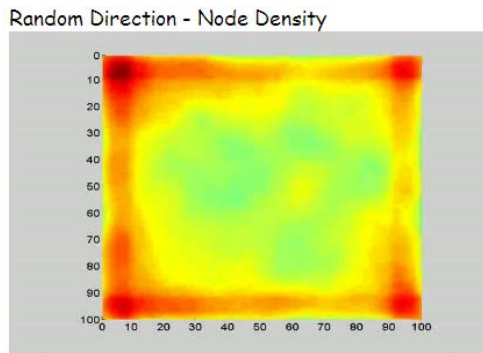
Figure 2- 8 Spatial node distribution of RD model

The characteristics that can be presented by Random direction model are direction, velocity, boundary, and pause time. Since the MNs always pause for a period of time at boundary, the average hop count of sending packets using Random Direction model is much higher than most of other models. It also means the connectivity of this model is lower than others. Improved Version of RD model is named as Modified Random Direction Mobility Model.[21] In this model, nodes select a direction degree as they did in Random Direction Mobility Model, but they may choose their destination anywhere along that direction of travel. They do not need to travel all the way to the boundary. This movement pattern can be also produced by adding pause time to RW model. From Figure 2-9, we can find that the average number of neighbors for this modified model is higher than that for Random Direction Mobility Model, which indicates a lower average hop count and a better performance of this modified model.
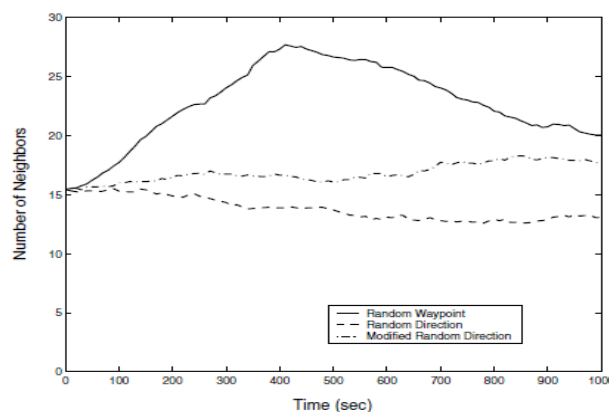

Figure 2- 9 Average Neighbors per Node at 1m/s Mobility[13]

2.3.4 A Boundless Simulation Area Mobility Model

There are 2 main improvements of this model. The first one is the variable velocity which is more realistic than previous models. Correlation exists between the previous states, which are velocity and direction, and the current states. The other one is the boundary limitation effect has been removed in this model.

In this mobility model, the designers used velocity and direction vector $\overline{v} = (v, \theta)$ to describe a MN's state. They use *(x, y)* as the position of a MN. These variables are updated in the below way after every time interval Δt. Here we can find the formulas of velocity *v*, angle *θ*, co-ordinate *x* and *y*.

$$\begin{cases} v(t + \Delta t) = \min[\max(v(t) + \Delta v, 0), V_{max}] \\ \qquad \theta(t + \Delta t) = \theta(t) + \Delta\theta \\ \quad x(t + \Delta t) = x(t) + v(t) \cdot \cos\theta(t) \\ \quad y(t + \Delta t) = y(t) + y(t) \cdot \sin\theta(t) \end{cases}$$

Where V_{max} is the maximal mobile velocity, Δv (the change of velocity) is uniformly distributed within $\left[-A_{max} \cdot \Delta t, A_{max} \cdot \Delta t \right]$, A_{max} is the maximum acceleration/deceleration of the MN, and $\Delta\theta$ (the change in MN's direction) is uniformly distributed in $\left[-\alpha \cdot \Delta t, \alpha \cdot \Delta t \right]$, where α is the maximal angular change of the direction of a MN per unit time. [15]

Also, we assume that the MNs are distributed randomly in a closed coverage area effectively creating a torus. The rectangular area on the left side of Figure 2-10 is transformed into the torus shape on the right side of Figure 2-10 in two steps; first we fold the simulation area so that the top border ($y = Y_{max}$) lies against the bottom border (*y = 0*), forming a cylinder, and then we fold the resulting cylinder so that both open circular ends connect. Thus, for example, a MN that "exits" the coverage area from the left side appears as reentering the coverage area on the right side with the same velocity and direction. Continuously movement without reflection or stop is admitted in this model. [15]
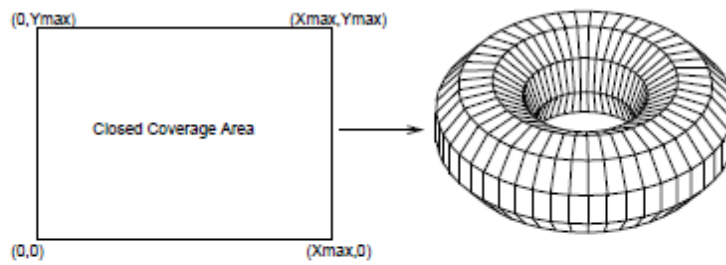
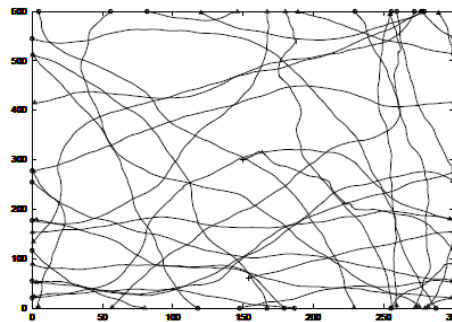Figure 2- 10 Coverage area mapped into a closed surface

Figure 8: Traveling pattern of an MN using the Boundless Simulation Area Mobility Model.

Figure 2- 11 Traveling pattern of an MN in the Boundless Simulation Area Mobility Model

In this model, the velocity and direction is recalculated at every time step by considering the realistic limitation of acceleration and direction change. Node can move continuously without pause in this model. And the change of velocity is uniformly distributed within the range of maximum acceleration*time interval.

Figure 2-11 shows us the traveling pattern of an MN using this mobility model; it's a more realistic than previous model. But it has 2 disadvantages. One is the undesired side effects that would occur from allowing the MNs to move around a torus. For example, one static MN and one MN that continues to move in the same direction become neighbors again and again. In addition, a simulation area without edges would force modification of the radio propagation model to wrap transmissions from one edge of the area to the other. [13]

2.3.5 Markovian Random Path model

This model is also designed to reduce the sudden movement of nodes. The movement of MN in this model is decided by a three-state Markov chain like this
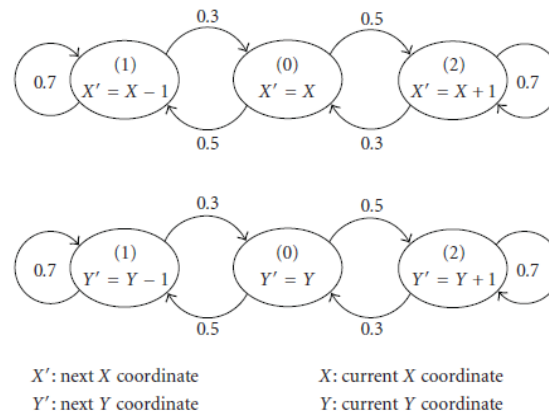
Figure 2-12.

X': next X coordinate   X: current X coordinate
Y': next Y coordinate   Y: current Y coordinate

FIGURE 2: MRP model.

Figure 2- 12 MRP model represetns 3 states-E_0, E_1, E_2.

The user changes direction according to the probability matrix.

The states of the MNs (for each direction, *x* and *y*) in this case represent the position variation and not the X and Y position themselves. The state-transition diagrams of X-direction and Y-direction will represent the direction changes of the MN. Initially, both X-direction and Y-direction are on state E_0; in the next step, going from E_0 to E_2 represents an increase in the respective coordinate, X or Y-coordinate, and a transition to E_1 will denote a decrease in the respective coordinate.[16]

It can't represent the horizontal or vertical movement, and forbids the MN from stops longer than one interval of time as well. Also, the MN in this model tends to remain its direction once it starts to move. The reason is the higher probability of staying in E_1 and E_2 than going back to E_0. [16]

2.3.6   Simple Individual Markovian mobility model

Previous model, Markovian Random Path model, doesn't allow horizontal or vertical movements. The pause time can't be longer than one time interval. Also the velocity in MRP model is a constant, which can't present the realistic mobility pattern of human.

The Markov chains of this model (Figure 2-13) are a little bit different from that in MRP model. In the figure, *p, q, 1-2p* and *1-q* are the probability of state change from previous state to next state indicated by the arrow.
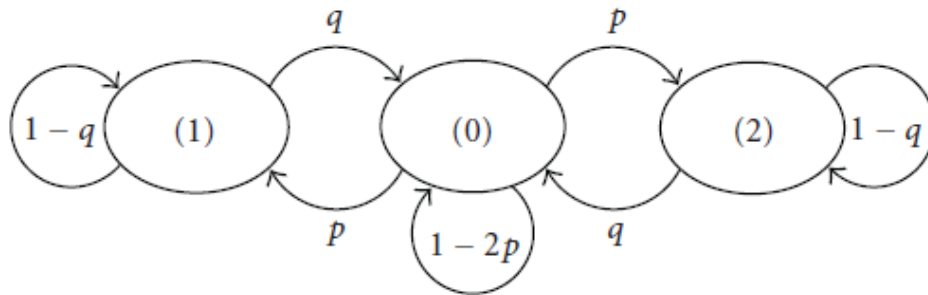

Figure 2- 13 State transition diagram for the Markov chains representing movement in the SIMM model (for both x and y directions)

As it can be observed, this model presents a new characteristic which is to allow transitions from *state (0)* to itself, with probability *(1−2p)* , thus assuming that MNs can remain in that state for one or more consecutive steps. The model allows every MN to remain still, that is, *x* and *y* remain the same in one or more instants of time.[16] The transition probability matrix can be easily calculated using the diagram in Figure 2-14.
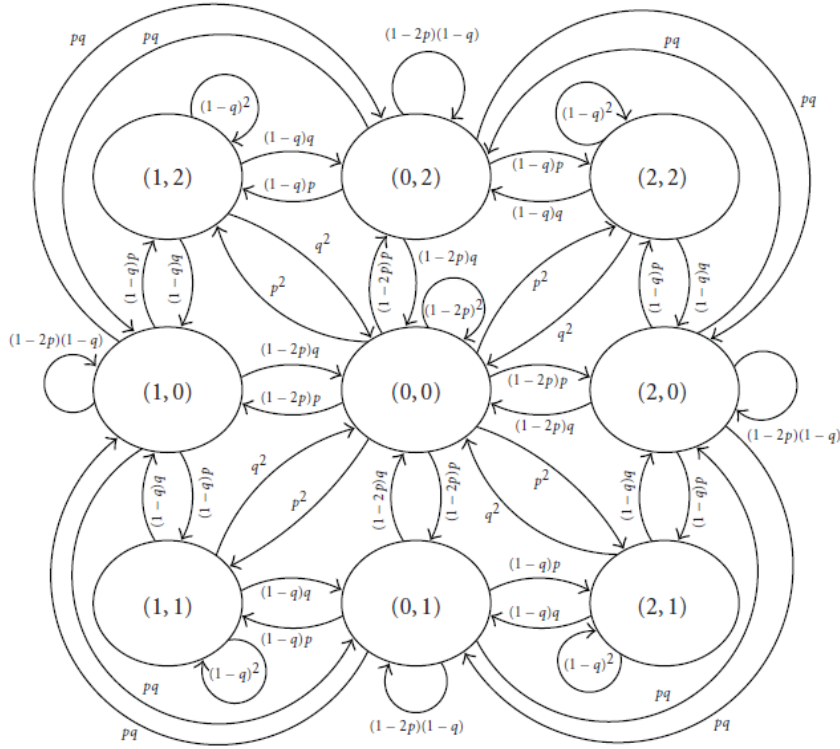
Figure 2- 14 Example of state-transition diagram for the SIMM model[16]

This model can present direction, velocity and pause time in a very limited way. It can only mimic 3 different velocity values. When the MN doesn't move, the velocity is 0. Another value occurs when the MN moves horizontally or vertically. The last velocity value takes place when the MN moves along the diagonal.

2.3.7 Gauss-Markov Mobility Model

To adapt to different levels of randomness via one tuning parameter, the Gauss-Markov mobility model has been designed.

MNs have initial speed and direction, at fixed time intervals n, speed and direction are updated for each MN. We can know from the character of Markov Chain that the value of speed and direction at the n_{th} instance are only decided by values at the previous instance *(n-1)*.

$$s_n = \alpha s_{n-1} + (1-\alpha)\overline{s} + \sqrt{(1-\alpha^2)}s_{x_{n-1}}$$

Equation 2- 2

$$d_n = \alpha d_{n-1} + (1-\alpha)\overline{d} + \sqrt{(1-\alpha^2)}d_{x_{n-1}}$$

Equation 2- 3

Where s_n and d_n are the speed and direction of the MN at time interval n, and $s_{x_{n-1}}$ and $d_{x_{n-1}}$ are random variables from a Gaussian distribution. $\overline{s}$ and $\overline{d}$ are constants respectively the mean value of speed and direction as n towards infinite. [13]

Intermediate levels of randomness are obtained by varying the value of tuning parameter α between 0 and 1. By using these parameters, the position of an MN at each time interval could be easily calculated.

When $\alpha = 0$, this model turns into Brownian motion.

When $\alpha = 1$, MN follows linear motion.

The constant $\overline{d}$ can be changed to prevent the MN stay near the edge of area for a long time.

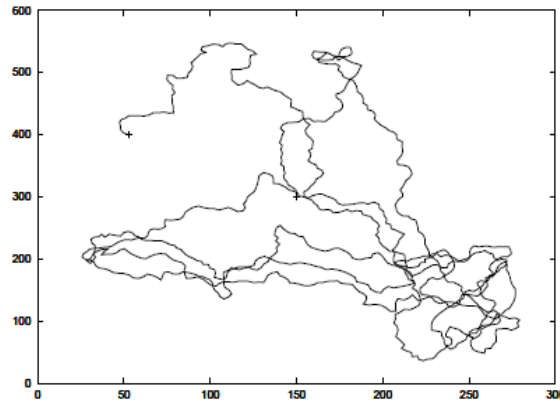Figure 2-15 is the trace of an MN using Gauss-Markov model.

Figure 2- 15 Traveling pattern of an MN using the Gauss-Markov Mobility Model[13]

Not only the problem of sharp turn and sudden stop has been solved by using this model, but also the variety of velocity has been considered in this model, which makes it a better model than MRP and SIMM model. It addressed the velocity and direction characters better. The node distribution of this model is similar to RWP

model, the node density in central area is the highest.

2.3.8   City Section Mobility Model

In the realistic situations, the travel pattern of MNs is restricted by the city section. MNs can't ignore the obstacles or traffic limitations like they did in all previous models. Furthermore, the route of an MN is regularly because human tends to travel in similar patterns in their daily life. The City Section Mobility model is presented on this consideration.

The simulation area is separated to squares by different kinds of roads. Instead of assigning a maximum speed to all MNs and varying this speed between simulations, the author assigned different speeds to mid-speed and residential roads. Each MN begins the simulation at a predefined intersection of two streets. An MN then randomly chooses a destination, also represented by the intersection of two streets. Moving to this destination involves (at most) one horizontal and one vertical movement. Upon reaching the destination, the MN randomly chooses another destination (i.e., an intersection of two streets) and repeats the process. In other words, the MN does not pause between movements. [13]

This model addressed more characteristics than previous models; the displacement, direction, pause time, and velocity are all considered.

The pause time fits uniform distribution between the predefined range $[0, t_{max}]$, average pause time is $t_{max}/2$.

The epoch time (travel time) of this model is shown in the Figure 2-16. This 3-dimension figure shows us how can 2 parameters (speed limit and number of avenues) in the model decide the travel time value of user.
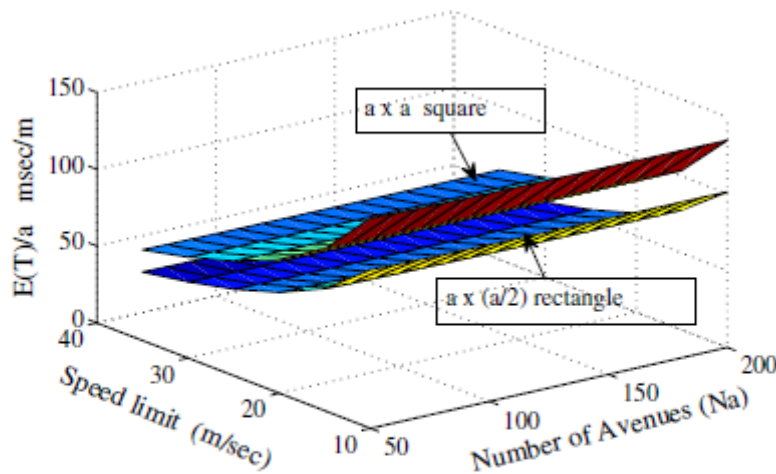
Fig. 3. Expected epoch time of CitySec mobility model as a function of speed limit and number of avenues (streets).

Figure 2- 16 Expected epoch time of CitySection mobility model as a function of speed limit and number of avenues(streets).[18]

It indicates that the travel time is independent with number of avenues, but related to the speed limit. Long travel time is caused mainly by the strict speed limitation.

Now let's move to the displacement distribution of this model. The average displacement is decided by the shape of simulation area (shape of city in real case).

The grids used in this model is obviously too simple to represent the real city environment. But it's quite hard, if not impossible, to get an accurate simulation area. Furthermore, this model needs to consider of adding pause times and the acceleration/deceleration to this model. The last issue is that the time-dependence of human mobility should also be studied.

2.3.9 Self-similar Least Action Walk Model

The mobility model introduced by [22] is a more accurate and realistic model for human mobility presenting.

By generating fractal waypoints first, SLAW implies that human tends to go to more popular places. Also the boundary of human mobility has been considered, SLAW develops an individual walker model to restrict the mobility of each walker to a predefined sub-section of the total area. This individual model is designed to fit

several features of human mobility:

- F1: truncated power-law flights and pause-times;
- F2: heterogeneously bounded mobility areas;
- F3: truncated power-law inter-contact times;
- F4: fractal (also called bursty, self-similar spread) waypoints.

According to this paper [22], F4 induce F1, heavy tail flights and F2 induce F3 [29].

First, SLAW generate fractal waypoints on simulation area, then use Least action trip planning(LATP) to calculate the plan the trip sequence among all the selected waypoints.

LATP and fractal waypoints may satisfy F1 and F4. To complete the trace generation process while satisfying F2 and F3, [22] combine LATP with an individual walker model. To enforce heterogeneously bounded walkabout areas among walkers, SLAW select a subset of fractal waypoint clusters and restrict the movement of each walker to its own designated set of clusters. These selected waypoints are compulsory for nodes. SLAW also selects some additional waypoints which is changeable for each walker every day. It shows that this walker model combined with LATP and fractal waypoints generate power-law ICTs (satisfying F3). [22]

This SLAW mobility model has considered preferred area, flight length, pause time and return time. But it didn't consider of the velocity& acceleration. The velocity was chosen when the simulation started and hadn't been changed during the simulation period. This means the model only represented the human mobility with constant velocity.

Another disadvantage of SLAW is the boundary area selection method. It's true that every node has been assigned a compulsory waypoints set as a preferred area. But according to the graph and the formula in [8], the radius of this area is mostly impacted by the distance between 2 positions which are visited by the node most often, i.e. home and office. This feature hasn't been considered in [22]. Therefore

the boundary area hasn't been set up in a realistic way in SLAW.

At last, the LATP is a better way to design path than previous models, but only the start waypoint as home in all waypoints dataset has been decided. Since there are additional waypoints for node to add randomness to its' movement, the places that a node needs to walk around changed every day. Now the situation is, for example, if waypoint W_1 represents home, W_2 represents office, and an additional waypoint W'_3 represents a cinema in the middle of W_1 and W_2, it's possible that the path calculated by LATP is W_1->W'_3->W_2. However, it is obvious that human will not have a sudden impulse to go to cinema and stay there for hours on the way to his office in most of the cases. On the other hand, if we can define both waypoints which represent home and office as the initial points, this problem could be solved. In real world, it means a human has to go from home to office first, after that, it can use LATP to calculate future path.

2.3.10 Working Day Movement Model

In paper [27] , a new mobility model which is a combination of several submodels has been designed. This model consists of 3 models to represent human daily activities and use a transport submodel to connect them.

Home activity submodel is used to represent the motionless state of mobile devices during night. After arrived at an assigned home location, the node moves a short distance and stay there till wakeup time.

Office activity submodel is designed to show the movement pattern inside an office. It assumes the employee has a desk and needs to meet colleagues from time to time. The office is entered from a specific point as a door. After the node reached the door, it walks to the desk of itself and pause for an amount of time which is drawn from a Pareto distribution. After that it selects a new coordinate randomly in the office and pause again. A parameter is added to adjust the movement pattern, which makes a node can also stay at its desk for a whole workday.

A more variable submodel is named evening activity submodel. After work time,

this submodel took place and separated all the nodes to groups according to their favorite meeting positions which are assigned to them at the beginning of simulation. The node choose whether it will attend the evening activity by predefine a probability parameter to it, then use transport submodel to get to the meeting position, wait there till all the group member arrived and start moving to present a random walk on the street. The group walk along the street for a certain distance and pause for a period, both of the characters are defined in settings. After all these activities, they split up and return to their homes.

It's necessary to explain the transport submodel too. There are 3 kinds of nodes in this submodel. Nodes that have the lowest velocity walk to their destinations by finding the shortest path. For the nodes that have cars, they move at a higher velocity but go through the shortest path also. Other nodes can use public vehicle which is the pre-defined bus routes.

The evaluation of this working day movement model shows the contact durations and fraction of nodes encountered were only slightly affected by map, which can be used as a proof about the human has a generic movement pattern. According to the results, the ICT, contacts per hour, and contact durations of this model is much closer to real data in [28].

There isn't any evaluation about the characters we discussed in section 2, but we can find that this model designed the pause time, return time, velocity and regularity in a realistic way.

2.4 Summary

From section 2.3, flight length is related to the average velocity, velocity increased with flight lengths, then from section 2.4, displacement have impact on direction change, long trip displacement caused frequently direction change. We need to discover the relationship between all these characters we discussed before.

In our opinion, with the increase of displacement, travel time will also be increased, but the return time won't be impacted much. Also, the velocity will be higher. We

can say the displacement is the first fact we should consider for the human mobility since it can add influence to several other characters. Then we check the figure of flight length, the invisible boundary exists in it. Therefore, we consider preferred area as foundation of human movement characteristics.

Now we have already discussed the main characters of human mobility. However, there are some points we need to state again. From section 2.1, 2.3, we can find the difference between [3] and [1][2][5], this can be considered in 2 different ways.

Firstly, character performance is pre-decided by scenario. In section 2.1, the reason that pause time fits lognormal distribution in [3], not power law distribution as other papers, is that particular scenario is considered in [3], which is a park. So it's reasonable that the result is different from other scenarios like campus or shopping mall.

Secondly, which is the main reason from my point of view, the measurement period of [3] is too short to be analyzed. The longest period is only about 20 minutes; most of the participators only need 10 minutes to go through this park. From that we can say it's a small park with only smooth paths according to the map. The measurement area is also too small to be enough. In this case, the dataset is not suitable to be used in statistic analysis.

As a conclusion, before we start the research, we have to consider these 2 points in the first place, otherwise the results could be influenced and misleading us.

3 Design of new mobility model

After we finish the analyzing about 6 main characteristics of human mobility and performance of existing mobility models, the importance and objective of designing a new mobility model is extremely clear. According to the current situation that none of the existing mobility models can represent characteristics of human mobility realistically, we will introduce a new generic model which can be used in different kinds of scenarios and capture most of the main characteristics of human mobility that we mentioned in section 2.2. That is our goal of this chapter.

The remainder of this chapter is organized as follows. Firstly, analysis of reasons that decide human movement pattern in Section 3.1. Secondly, introduce the proposed mobility model's foundation, which is radius of preferred area, in Section 3.2. Also we will analyze the self-similar performance of node dispersion and visit points' distribution in Section 3.3. Finally, our mobility model can be constructed step by step in Section 3.4 and therefore summarized at last Section 3.5.

3.1 Consideration and Goals of new mobility model

In previous chapter, the main characteristics of human mobility have been discussed in details. In this section, the factors that can decide the movement pattern will be listed. They are physical condition, psychological reason and environmental information.

In previous papers, the impact of these factors has been mentioned briefly by one or two sentences, i.e. there is a kind of mobility prediction method has considered the first factor-physical condition in [12], the prediction trajectory has been proved to be quite accurate comparing to other methods. A mobility model that has considered the city plan which can be summarized as environmental factor is put out in [13]. But none of the papers has discussed them systematically.

3.1.1 Physical Condition

The first factor is physical condition of human, which can be specialized as which

kinds of vehicle the human used for travel. We can see from the graph, when human is walking, the maximum velocity is no more than 3m/s. Velocity higher than this value means the usage of vehicle, then the movement speed of human is decided by the condition of that vehicle, i.e. a car is much faster than a bicycle. Also, human walk has lower up-bound of acceleration than vehicle. Therefore the travel time is under the impact of physical condition either. The physical condition could be an important factor used to predict human movement.

The direction angle change of human movement is also impacted by the physical condition. Consider the situation that both a high speed car and a walking human in a place without any obstacle, in which case the human can change his direction more than 90 degree without slowing down, but the car can't. To finish a sharp turn, the velocity of car has to be decreased significantly. And if the car needs to drive to the opposite direction, it has to move several meters on perpendicular direction in a lower velocity. This can be noteworthiness in an detailed analysis. All these limitations are caused by the physical condition.

That is why we need to consider physical condition or limitation as one of the basis factors of movement pattern.

3.1.2 Psychological Reason

During the analysis of spatial performance, a significant phenomenon can be seen, which is the existing of preferred area. This can be considered as a result caused by psychological reason.

Many people tend to be active mostly in their familiar area in a regularity way, which is understandable if we think about it with psychological consideration. In most of the case, the radius of this area is related to the distance between their home and workplace.

From the paper [8], we can see that the human movement area tends to be narrower when this person is active in a larger area. We can assume a man who has to travel a long distance to go work every day. There are 2 reasons that can cause this narrow

shape. The first is that human tends to avoid the uncomfortable experience, which means to minimize the travel length in our case, i.e. it makes sense if he always went to the nearest supermarket on his way home. The second reason is when the diameter of human active area is long, it could be referred to a long distance between home and workplace; it will be easier for that man to find all facilities he need along the direct line between his 2 most favorite places-home and workplace.

Another phenomenon caused by psychological reason is the absence of sharp direction change for short displacement. Human tends to select the direction before the movement starts and always moves along the selected direction until an obstacle block his way. However, for long displacement, it is unlikely to find a direct line from start position to the destination, so the human trace will be decided by the environmental information.

We can say that return time is the third characteristics impacted by psychological reason. The peak of return probability emerged every 24 hours is caused by the human habit of going home every day unless they are living a vagrant life.

3.1.3 Environmental Information

The last factor that can decide the human movement pattern is the environmental information. As we have noticed from section 2.2.4, the change of direction is related to the shape of city roads. In an environment with rectangular structure, the mostly happened direction change is 90 and 270 degree, which indicates lots of perpendicular turnings at each crossroads.

Another fact is that the speed limitation of road is the upper bound of velocity no matter how fast the selected vehicle can reach. As for the high speed road, a lower bound of velocity should also be added into consideration.

Displacement and pause time is related to the environment too. If we are observing the human movement pattern in a shopping centre, the displacement and pause time are both very short. But if the observation environment is a campus, the displacement depends on the buildings' locations and the pause time values are

related to the schedule of university.

All these factors are particularly useful during the preparation period of mobility prediction or model's design. Knowing the weight of these factors can help us to produce a method which is more realistic and accurate than before.

In Section 2.3, we can find the performance and disadvantages of existing mobility models. Basically, none of them can fit all 6 main characteristics of human mobility. To be specific, the best situation is 3 realistic characteristics for one mobility model.

In that case, our new mobility model can be considered as a more accurate model than others if we can fits 4-5 characteristics of human mobility.

After the 3 reasons that can impact human trace have been listed, we decide to use invisible boundary characteristic of human movement as a start point of our model.

3.2 Foundation of mobility model

Invisible boundary exists in human life; this can be defined as the psychology reason of characteristics of human mobility. However, it's necessary to translate this psychology reason to equation that we can use in model construction.

According to the definition of preferred area in [8], the radius of preferred area is the parameter we need as a mathematics translation of invisible boundary. Therefore, we will use this characteristic as a foundation of this thesis.

The radius of preferred area *(km)* is defined as follow:

$$r_g = \sqrt{\frac{1}{\sum_{i=1}^{n} pt_i} \bullet \sum_{i=1}^{n} \left[pt_i \cdot \left(\vec{r_i} - \vec{r_c} \right)^2 \right]}$$

Equation 3- 1

In which the $\vec{r_c}$ is defined like this:

$$\vec{r_c} = \frac{1}{\sum\limits_{i=1}^{n} pt_i} \sum\limits_{i=1}^{n} \left(\vec{r_i} \cdot pt_i \right)$$

Equation 3- 2

$\vec{r_i}$:the location of i=1,…,n$_{th}$ visit point.

pt_i :pause time at the i$_{th}$ visit points.

The radius of preferred area fits this truncated power-law equation. Define the radius as r_g and the probability density function of r_g is:

$$P(r_g) = (r_g + 5.8)^{-1.65 \pm 0.15} \exp(-r_g / 350)$$

Equation 3- 3[8]

Our method is to select r_g values according to this equation, then for each user, finish all other steps based on this assigned value. After all the steps have been finished, we can re-calculate the new r_g' values for all users, to check that whether they still fit truncated power-law distribution.

3.3 Self-similar

What is self-similar? In mathematical explanation, a self-similar object is exactly or approximately similar to a part of itself (i.e. the whole has the same shape as one or more of the parts). In our case, we consider the self-similarity, which is also named as bursty manner or fractal in this thesis, of points' dispersion pattern in a given area.

The method used to evaluate the self-similarity according to [22] is listed here:

1. Divide the whole area to squares with size d^2 (equal to the resolution in Figure 3-1).

2. Calculate the Variance of $\dfrac{\text{Number of points}}{\text{Square size d}^2}$

3. Increase the d value, the variance trace can be estimated as a straight line with decreasing slope a.

4. Define Hurst parameter as $H = 1 - a/2$.

In this thesis, Hurst parameter is a single parameter that characterizes a self-similar process, therefore be used to check the self-similarity of visit points' distribution. When Hurst parameter H=0.5, it means that the distribution of points in simulation area is pure random, this is the lower bound of Hurst parameter in this case. 0.5<H<1 means the distribution of visit points has bursty manner, which indicates the number of points in each part of the area has uneven performance. Here we will use a figure in [31] as an example of how can we analyze the self-similar performance and what kind of curve can we find after we use the method listed before this paragraph.
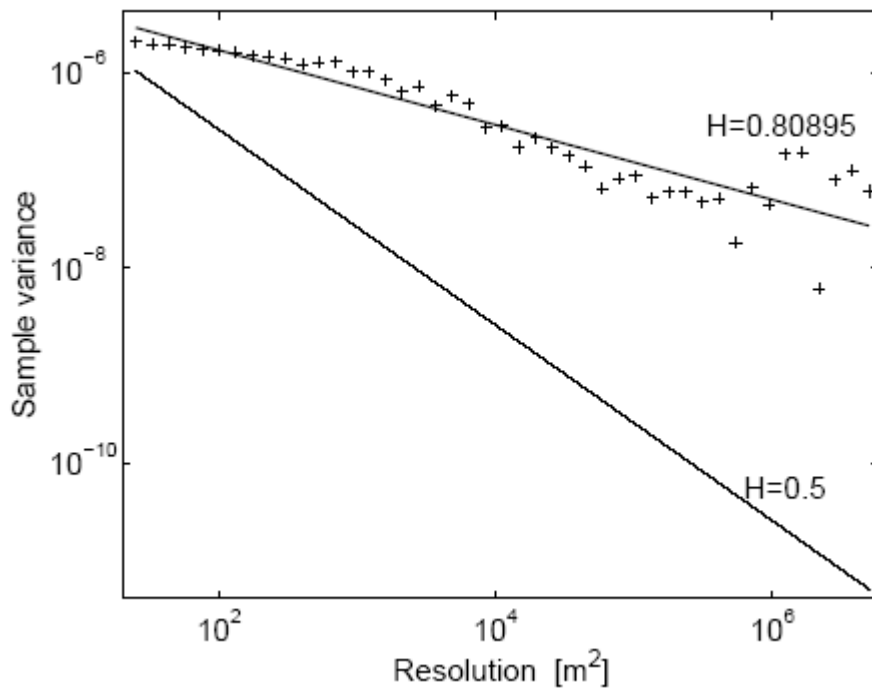
Figure 3- 1 The Hurst parameter estimation of visit points in [31]

In [31], first the researchers discuss the distribution of all visit points they recorded, according to the Hurst parameter, the visit points of all participators have the self-similar performance.

The initial locations of users could be equalized as some visit points randomly

selected from all the visit points recorded for all users. It means that the initial distribution of users in our model will have self-similar performance. There is also a psychological reason for this phenomenon: "Popular place tends to be more popular."[1]
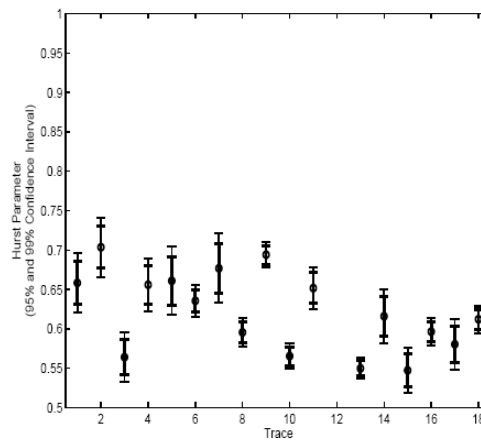
Then they evaluate the distribution of visit points for each individual users, the Hurst parameter calculated in this paper also indicates the self-similar performance of individual user's visit points.
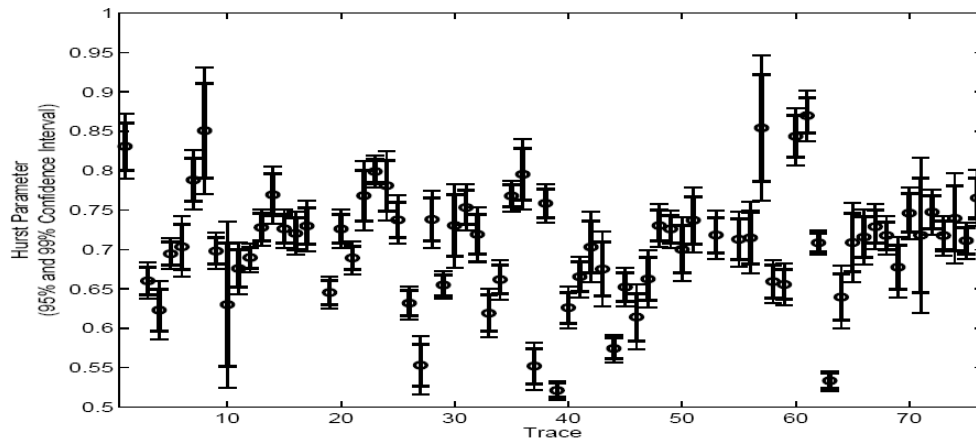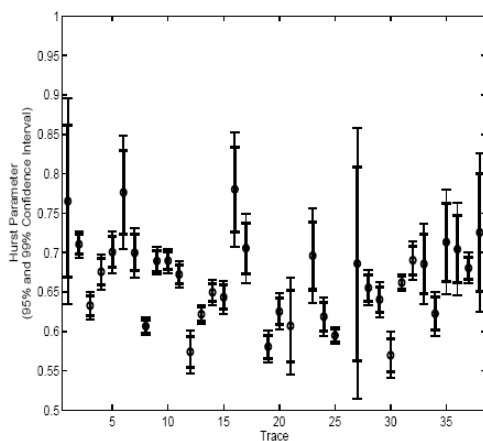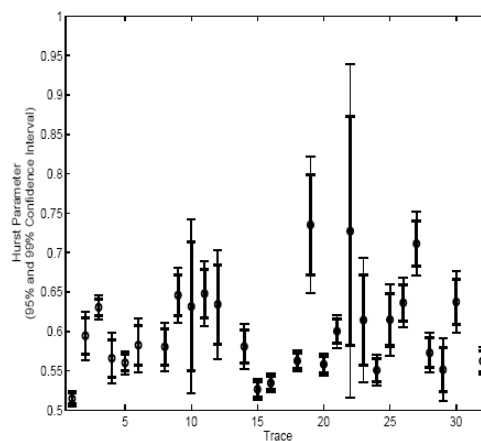
(a) KAIST
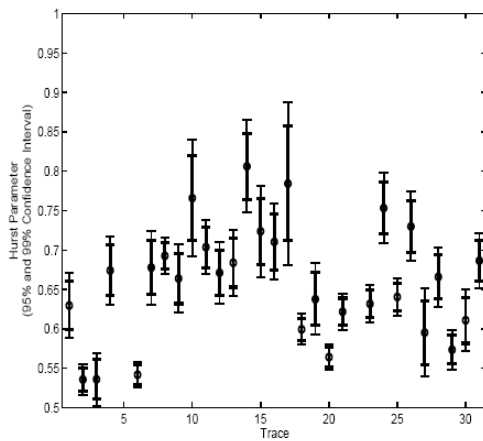
(b) NCSU

(c) State fair

(d) Orlando

(e) New York City

Figure 3- 2 Hurst parameter values of visit points of individual users[30]

According to Figure 3-2, it is reasonable for us to consider individual user's visit points as self-similar distributed, this fact is another important basement of our new mobility model. The Figure 3-2 is acquired from other research group of [30], however they never used the self-similarity of individual users' visit points in their mobility model. The difference between our model and SLAW is that in this thesis, the self-similar performance of individual user's visit points will be considered instead of the aggregated visit points of all users considered in SLAW.

3.4 Design of new mobility model

Before we start this section, we will use some abbreviations to represent 6 main characteristics of human mobility:

- *C1 (Pause time):*
  - o Pause time of users staying in one position continually fits truncated power law distribution
- *C2 (Return time):*
  - o Return time of users presents peaks after every 24 hours
- *C3 (Velocity):*
  - o Velocity is related to the flight length
- *C4 (Angle change):*
  - o The pdf of direction angle change reaches the maximum value at 90 and 270 degrees
- *C5 (Flight length):*
  - o Flight length fits truncated power law distribution
- *C6 (Radius of preferred area):*
  - o The radius of preferred area fits truncated power law distribution

This new mobility model is specified as 5 steps, each step is explained as follows:

- *First step:*
  - o Decide the users' initial positions according to self-similar characteristic of users' distribution.
- *Second step:*
  - o Assign preferred areas to these users according to the equation listed in Section 3.3, and by this step, the model will fit c6.
- *Third step:*
  - o Decide visit points and pause time for each user, to fit c1 and c2.
- *Fourth step:*
  - o Aims to plan the path in a realistic way, and it will fits c5.
- *Last step:*
  - o Find realistic velocity value to fit c3.

The steps are organized in this sequence for several reasons.

In our mobility model, we try to fit the characteristics of human mobility from users' distribution in whole simulation area to details for each user. So the first step should be distributing all users in simulation area, therefore we can have a general idea about how users are initially spreading in a given place.

Then we consider the factor that the invisible boundary exists and shows the affection to several other characteristics, if we can capture the property of preferred area accurately, the performance of our mobility model could be improved. That is the reason that we assign preferred area to each user in second step.

After that, we consider the self-similarity again but this time for individual users, so we generate possible visit points with bursty manner for each user in their preferred area and select some of them as the destinations of a user. But we need to add the definition of preferred area into consideration, the radius of preferred area is calculated by the coordinates of each visit points and pause time values of each position. Therefore we need to add an adjustment procedure to make sure that the new calculated r_g' according to the selected visit points is close to r_g.

Now we have the visit points and pause times of all users, next step will be the planning of trace. We use the fact that human tends to move to the closest destination first unless another destination has higher priority.

At last, when users start to move, the velocity for each segment in whole trace should be selected according to the correlated flight length.

3.4.1   Step 1: Users' initial positions

The method is to generate users' initial positions with self-similarity (bursty manner).

Divide the simulation area to N square segments of equal size (i.e. $N=4$), put n users in N segments and make the synthetic variance equal to the real variance. According to Figure 3-1, the relation between square size and sample variance can be estimated to a straight line in log-scale coordinates.

V_0 is the minimum value of variance when H equal to 0.8, Figure 3-1.

d is the initial side length of simulation area before it has been divided.

A straight line in log-scale coordinates: $\log f(x) - V_0 = -a(\log x - d^2)$ can be used to generate the real variance function $f(x)$ of different segment size x:

$$f(x) = 10^{[(2H-2)(\log x - d^2) + V_0]}$$ Equation 3- 4

According to Figure 3-1, Hurst parameter H is defined as 0.8.

Use the figure as an example, for a square whose size is $d^2\,(\mathrm{m}^2)$, when we divide it into 4 segments, the surface of each segment is $d^2/4$.

Check Equation 3-4, when $x = d^2/4$, calculate the value of $f(x)$.

$n_{1,\dots,4}$: the number of users in 4 segments after first division.

Make the variance of $n_{1,...,4}$ equal to $f(d^2/4)$.

Then we separate each segments again and still make sure that the variance of users in each segment fits the Equation 3-4.

After several times, the size of each segment will be extremely small, at that time , if the number of points in a segment calculated by equation is *x*, randomly select *x* positions in this segment, the error will be too small to have influence of results.

3.4.2 Step 2: Assign preferred areas to users(C6)

The second step is to assign r_g values to all users.

Select r_g values to fit truncated power-law distribution, assign them randomly to n users, then generate *n* preferred areas.

Initial position of each user need not to be the center of preferred area, but should be inside the circle. That is because the center of a preferred area is unnecessary to be a visit point of user.

For each circle, draw a circumscribing square out of it. Therefore we can spread the visit points of individual users in their square at next step by using the same method as step 1.

The reason of this step is obvious according to Section 3.3, the radius of preferred area fits this truncated power-law equation.

3.4.3 Step 3: Distribute visit points and select pause times for each user (C1,C2)

The third step is to decide visit points for each user and select correlated pause time values.

In each user's square, spread *k* visit points like step 1.

For an individual user i, select m compulsory visit points from k visit points($3<m<6$, this is an experience boundary), which is a m-combinations of a k-element set. Then we select m pause time values to fit truncated power-law distribution.

Since there are $m!$ ways to assign t_i to point $_j$, now we have q ways to decide visit points and pause times for one user i.

$$q = \binom{k}{m} \cdot m!$$ Equation 3- 5

Since r_g is decided by pause time and positions, after we assign visit points and pause time to each user, we can calculate a new r_g', which is not equal to predefined r_g, to make new r_g' as realistic as r_g, we need to make sure the r_g' is as close to r_g as possible.

The method is to calculate $r_{gi1}',...,r_{giq}'$, according to the definition's equation in Section 3.3. Find the one to minimum $\left| r_{gij}' - r_{gi} \right|$, this r_{gij}' indicates its related group of selected corresponding time and coordinates values as the best estimated situation of user i. Therefore we can decide the ideal visit points and pause time's selection.

Human daily trace is regularly, user will repeat his trace after 24 hours, so we should add all the pause time and travel time, to make it close to 24 hours.

3.4.4   Step 4: Path plan for each user (C5)

After we have decided all visit points for every individual user, we will continue with step 4 which aims to plan the path.

Use Least action trip plan (LATP) algorithm to calculate path.

At current position i, the probability of select position j as the next destination is:

$$p(ij) = \frac{1/d_{ij}^2}{\sum_{k \in v-v'} 1/d_{ik}^2}$$

<div align="right">Equation 3- 6[1]</div>

d_{ij} is the distance between current position to the j_{th} point. When d_{ij} is larger, the probability of select j as next destination is lower.

V: set of all visit points

V': set of already visited points

The reason is that experts believe that human tend to minimum the displacement to avoid uncomfortable situation. Research [30] suggests that this fact together with unevenly spread visit points can generate truncated power-law distributed flight lengths.

3.4.5   Step 5: Select different velocities for different flight lengths (C3)

The last step, we select different velocities for different flight length.

Now we know the path and we know all the flight lengths value during the movement.

Every time when the user is leaving previous visit point, calculate the next flight length and assign an estimated average velocity to user according to Section 2.2.3.

According to the log-scale figure, for a longer flight length, user has a higher velocity, furthermore, the curve of velocity and flight length can be estimated to 2 straight segments, use l_{th} as a threshold, if the flight length is shorter than l_{th},

$$\log v(fl) = \frac{5}{18}(3 \cdot \log(fl) + 1)$$

<div align="right">Equation 3- 7</div>

In this equation, fl means flight length (m), v is the velocity (m/s).

Else if flight length is longer than l_{th}, the velocity of this trace segment is estimated by this equation:

<div align="center">48</div>

$$\log v(fl) = \frac{5}{18}(40 \cdot \log(fl) - 80)$$ Equation 3- 8

Since the real data is unreachable, the equation is abstracted from the figure by experience.

3.5 Summary

We have analyzed the reason of human mobility behavior and introduced the 5 steps of building a new mobility model in this chapter.

First we consider the human mobility pattern is decided by 3 aspects, the physical condition, psychological reason and environment information. According to the analysis, we find that preferred area is an important aspect of human mobility and has influence on several other characteristics.

Then we use this conclusion and consider the distribution of preferred area's radius as a basement of our model design.

Furthermore, self-similarity is another important aspect we need to consider and use to distribute users and visit points of individual user.

After that, the 5 steps of our mobility model are represented, we explain the basic idea of each step, the characteristic aims to fit in each step, and the detail method of this mobility model.

To conclude, the parameter of our mobility model can be adjusted to fit different scenarios, and the results of our model should fit 5 characteristics of human mobility theoretically. We will simulate and prove our results in chapter 4.

4 Implementation and Evaluation

In Chapter 4 we will explain the implementation of our mobility model, various experiments and simulation results, which include the performance analysis and comparison between mobility model and characteristics of human mobility.

Firstly, we explain the implementation of mobility model in MATLAB and various simulation scenarios used to evaluate the performance of model.

After that, the performance of new mobility model is discussed. While the existing mobility models have been proved to be different from real data of human mobility, we will focus on evaluate the performance of our proposed mobility model in various simulation scenarios with different parameters and compare them with the characteristics we discussed in chapter 2.

Based on the simulation results, our mobility model can be proved as a more accurate and realistic one than others. 5 characteristics of human mobility can be satisfied by using our mobility model.

4.1 Implementations

Our mobility model is simulated in MATLAB for analyzing the performance. In this section, we present the simulation setup of mobility model and offer various simulation scenarios, which are used to evaluate the performance of our proposed schemes.

4.1.1 Simulation Setup

Simulation is a practical and important way to validate and evaluate mobility model. By using MATLAB, the trace of users' movement can be generated. The statistic performance of 6 main characteristics can be calculated by using the simulation results.

- First we assign side length of simulation area and the number of users in MATLAB.

  These 2 parameters can be adjusted to represent different scenarios.

  Spread users in simulation area, set Hurst parameter (introduced in section 3.3) to 0.8 according to Figure 3-1. The result is a matrix contains n initial coordinates of n users.

$$\begin{bmatrix} x_1 & y_1 \\ \vdots & \vdots \\ x_n & y_n \end{bmatrix}$$

- Assign n radius of preferred area's values to n users according to the function in section 3.5.2.

  Now the results is $\begin{bmatrix} x_1 & y_1 & r_{g1} \\ \vdots & \vdots & \vdots \\ x_n & y_n & r_{gn} \end{bmatrix}$

- For individual user i, generate k visit points and m pause time values which follow truncated power law distribution, select m visit points and corresponds pause time to ensure the new-calculated r_{gi}' close to pre-assigned r_{gi}

  Therefore we have n matrixes for n users. For example, user i has a matrix contains the visit points and pause time at each point of one day.

- Use the method in section 3.5.4, step 4, to organize the sequence of these visit points.

  Now we have an organized matrix which includes the coordinates that the user will visit in sequence and pause times at each location.

$$\begin{bmatrix} x_{i1} & y_{i1} & pt_{i1} \\ \vdots & \vdots & \vdots \\ x_{in} & y_{in} & pt_{in} \end{bmatrix}$$

- Using this information, we can calculate the displacement orderly, and select corresponding velocity for each flight length.

- At last, for each user, we have a final matrix that contains the whole information of his movement in 24 hours.

- Then repeat previous steps from step 3, change several visit points as selective visit points of this user to add some randomness to his trace.

4.1.2 Define scenarios

	Simulation area(m*m)	Group of users	Amount of users
Area 1	200*200	Group 1	50
	200*200	Group 2	200
Area 2	800*800	Group 3	100
	800*800	Group 4	500
Area 3	2000*2000	Group 5	800
	2000*2000	Group 6	5000

Table 4- 1 Simulation scenarios

We will use these scenarios for performance analysis.

- Group 1:

  The first group indicates a small area with few users, for example, a park, a farm.

- Group 2:

  This group represents a small area with more dense users' dispersion, for

example, a conference, a cinema, or a library.

- Group 3:

  The third group aims to simulate a middle size area with sparse user distribution. Like institute with large equipments but few people to operate them. Or a forest is also suit for this scenario.

- Group 4:

  A middle size simulation area with many users can be used to simulate a shopping mall or the centre of a small city.

- Group 5:

  A large simulation area with only 800 users in it, this can indicate the situation like a farm.

- Group 6:

  This scenario represents the largest simulation area with lots of people in it. It can be used to simulate the movement of students in a campus.

4.2 Performance Analysis

In this section, we will analyze the performance of our mobility model based on the conclusion we made in chapter 2 about human mobility.

4.2.1 Visualization of self-similarity

First, we use 4 groups of users (group 1,3,4,6) in different simulation area size as an example about how users are initially distributed in a self-similar way.
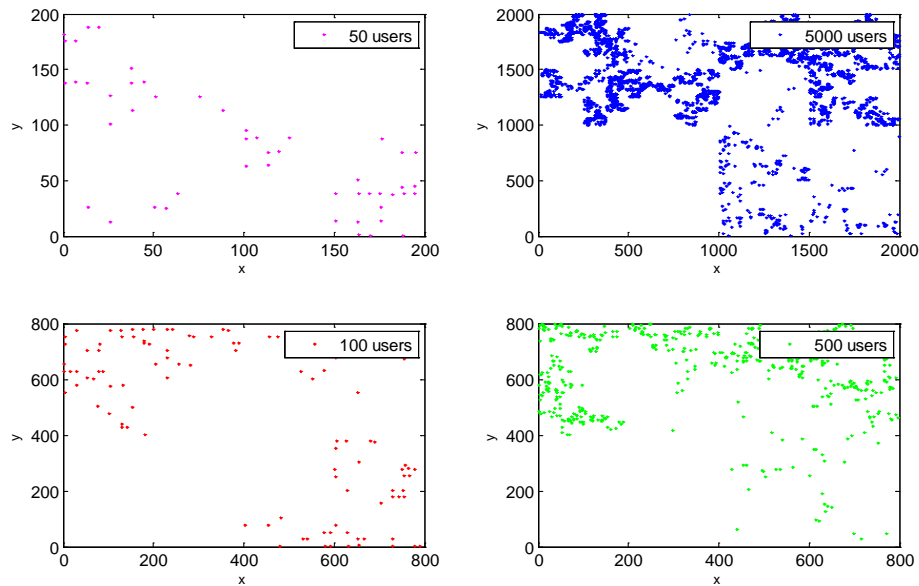
Figure 4- 1 Distribution of users in different area

The uneven distribution is obvious from the Figure 4-1. When we adjust the side length or the number of users, this uneven performance remains the same.

To explain this figure, we can assume different scenarios to find the relation between these figures.

For example, when we analyze the figure of 800m*800m with 500 users in it, it can be considered as users in a city center, the dense part of simulation area can be considered as hot zones of this area (station, popular stores).

Another one is the figure of 2000m*2000m with 5000 users in it, which can be treated as an university, the dense part can be considered as a special place like library/sports centre/ teaching facilities and so on, these are the places that students tends to aggregated.

Basically the uneven performance exists in most of scenarios we can think about. And our mobility model can represent it clearly.

4.2.2 Radius of preferred area
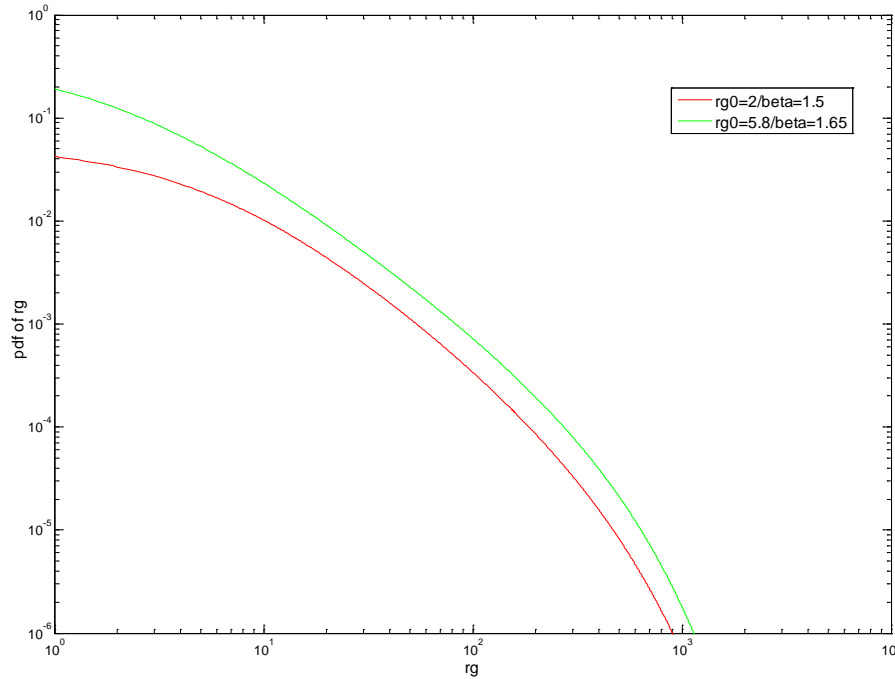
Figure 4- 2 Pdf of rg with different parameter values

Here are 2 curves which represent different parameters of r_g's equation according to [8],

$$P(r_g) = e^{-r_g/350} \cdot (r_g + r_{g0})^{-\beta}$$
<div align="right">Equation 4- 1</div>

the parameters r_{g0} and β can be adjusted to find the best fitness. In Figure 4-2, the label of 2 curves indicates the value of r_{g0} and β used in each curve.

Compare them with Equation 3- 9 (represented as the red curve in Figure 4-2), the green line has a closer shape to the result in [8] . Since we don't have the real data, this is an experience conclusion according to the estimation and comparison of start point and end point in the figures.

Therefore, we use equation as follow instead of the given Equation 3- 10 in [8].

$$P(r_g) = e^{-r_g/350} \cdot (r_g + 2)^{-1.5}$$

Equation 4- 2

Therefore, we first assign r_g values to users to make sure the distribution of these r_g fits truncated power-law distribution.

Then in step 3, we distribute visit points for each user to make the re-calculated r_g' similar to pre-assigned r_g.

When we check the results of $\left| r_g' - r_g \right|$, the error value is too small to be indicated on the figure, which means the re-calculated r_g' is equal to r_g, the r_g' fits truncated power-law distribution in the same way as we expected according to characteristics of human mobility in section 2.2.6.
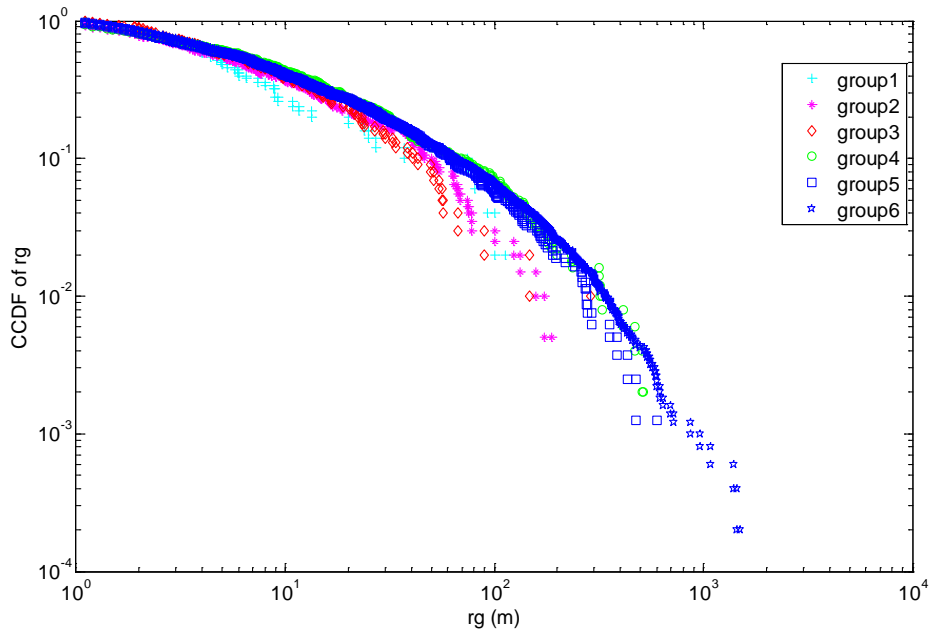
Figure 4- 3 CCDF of r_g' for different groups

In this figure, the curves indicate CCDF of re-calculated r_g' generated in our mobility model. These curves fit truncated power law distribution.
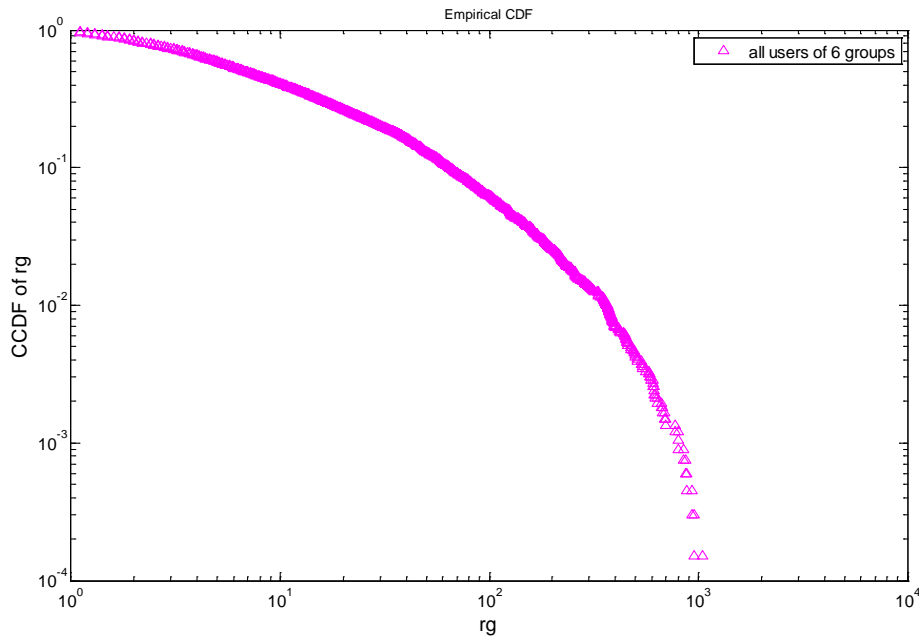
Figure 4- 4 CCDF of aggregated r_g' values for all 6 groups

Here is another figure of r_g' distribution for all the users in 6 groups. It shows us that when we aggregated different scenarios of our model together, the r_g' still fits truncated power-law distribution. The performance of this characteristic remains the same in most of situations.

Now we need to compare our model with existing model on this characteristic r_g.

According to [8], the r_g of Random Walk model is not realistic because the r_g value constantly increases together with the simulation time t.

Then we consider the r_g of Random Waypoint model. In an 800m*800m simulation area, randomly select a user, set pause time to 1 min. The Figures below show us that after a period of simulation time, the center of preferred area becomes very close to the center of whole simulation area.
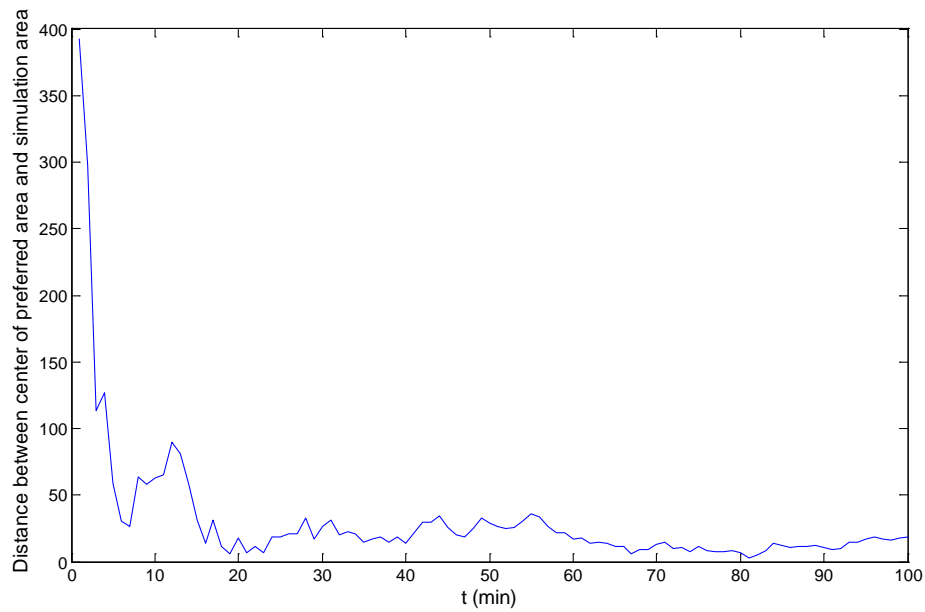
Figure 4- 5 The distance between center of preferred area and simulation area for individual user in RWP model.

Another fact about RWP model is that the r_g of individual user decreases first and becomes stable after a period of time. This phenomenon is reasonable, because for a node in RWP model, the probability of it selecting a position in center area is higher than boundary area. This figure also can be used to prove that nodes in RWP model tend to cluster at the center area.
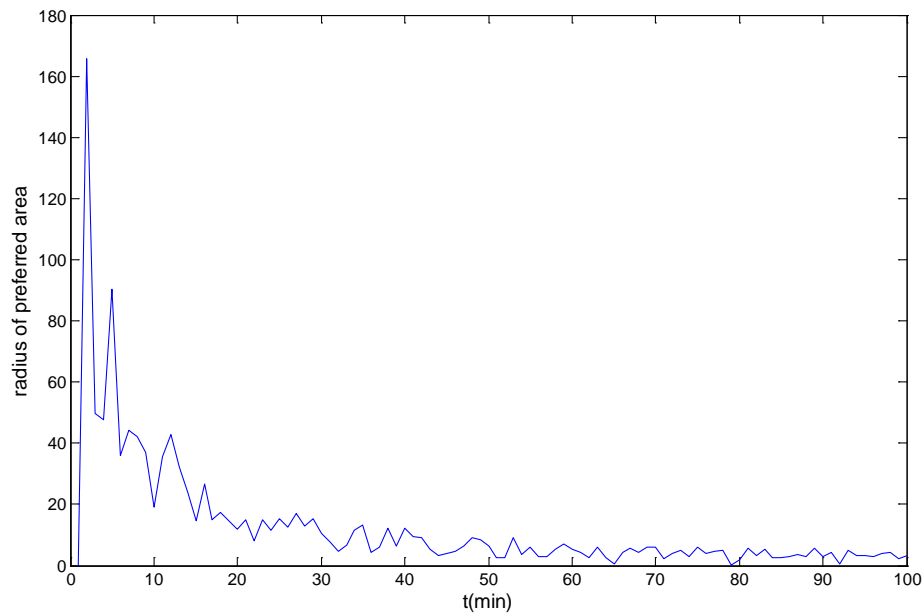
Figure 4- 6 r_g of individual user at simulation time t in RWP model

4.2.3 Pause time
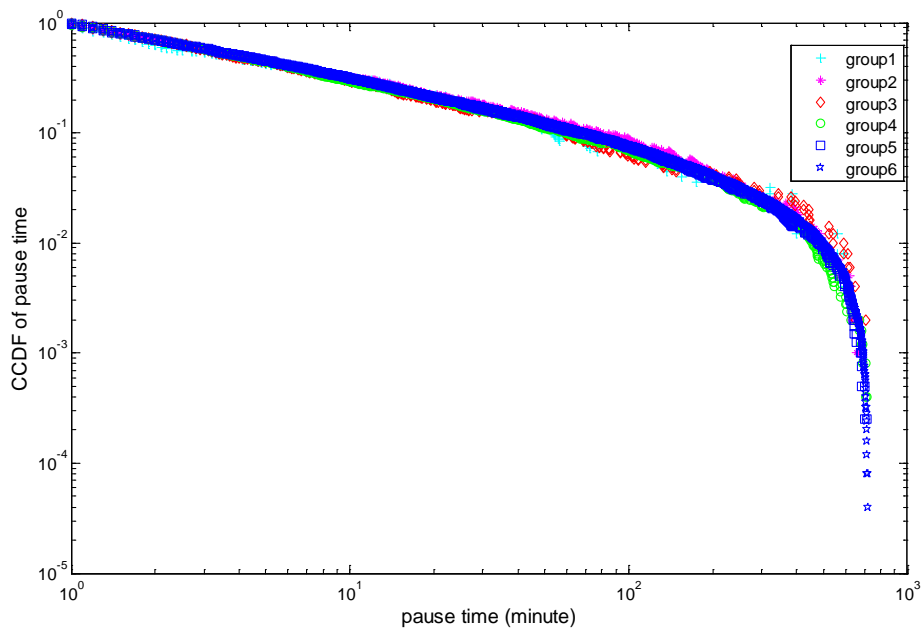
Figure 4- 7 CCDF of pause time for 6 groups

Figure 4-5 shows us the pause time distribution for users in 6 groups. Since we

select pause time to fit truncated power-law distribution, the curve here should also fits truncated power-law distribution.

However, an aspect which should be considered as variable is the fact that we have adjusted the pause time of user's initial position when the user return to it, to make the return time fits 24*n hours.

For example, when a user's trip has been decided to be A->B->C->D->A, the pause time that the user stay in A for the second time is adjusted to make sure that $\sum$ pause time of A+B+C+D+A=24 hours.

Therefore, the distribution of pause time needs to be analyzed.

Now the curves in Figure 4-5 are the distributions of pause time values which have been adjusted to support our model. We can find that they fit truncated power-law distribution either.
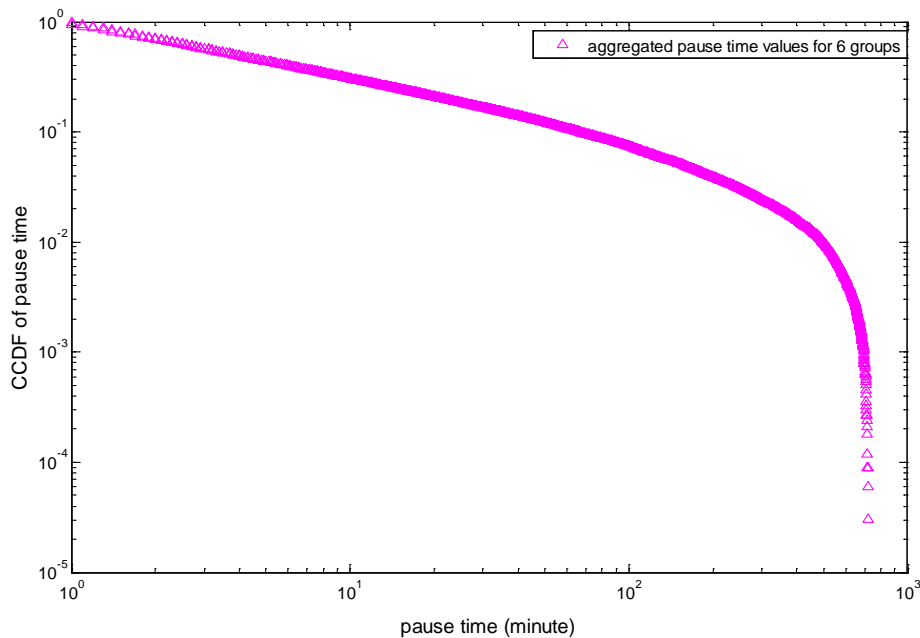
Figure 4- 8 CCDF of aggregated pause time values for all 6 groups

The aggregated pause time values for all users of the 6 groups also fit truncated power-law distribution, compare to the conclusion in section 2.2.1, our model also

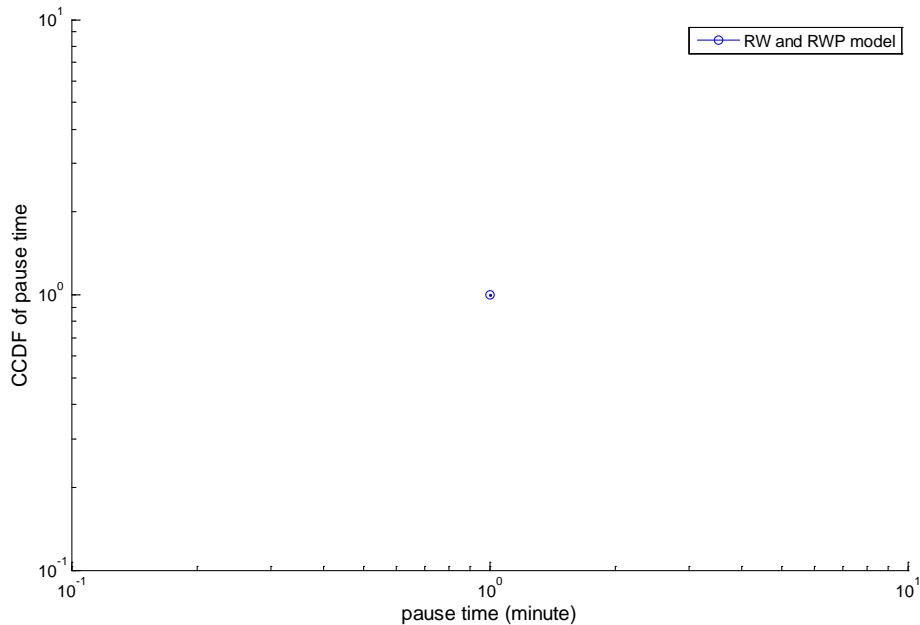can represent this characteristic in a realistic way.

Figure 4- 9 CCDF of pause time(Both Random Walk and Random Waypoint model)

Here we also draw a CCDF figure of Random walk and Random Waypoint mobility model. According to the definition, the pause time value is a constant value for both of these 2 models. For example, we set the pause time to 1 minute for these 2 models, the CCDF of pause time is not a curve, just a single point. Therefore, the performance of our model is better.

4.2.4 Return time

According to our design, the return time is pre-defined as 24 hours, this factor can't be affected by parameter adjusting during the simulation, the probability of finding the user in its' initial position after every 24 hours will be 100%.

This is not exactly the real situation, because incidents do exist in real life, but it's similar enough to assure the return probability peaks after every 24 hours.
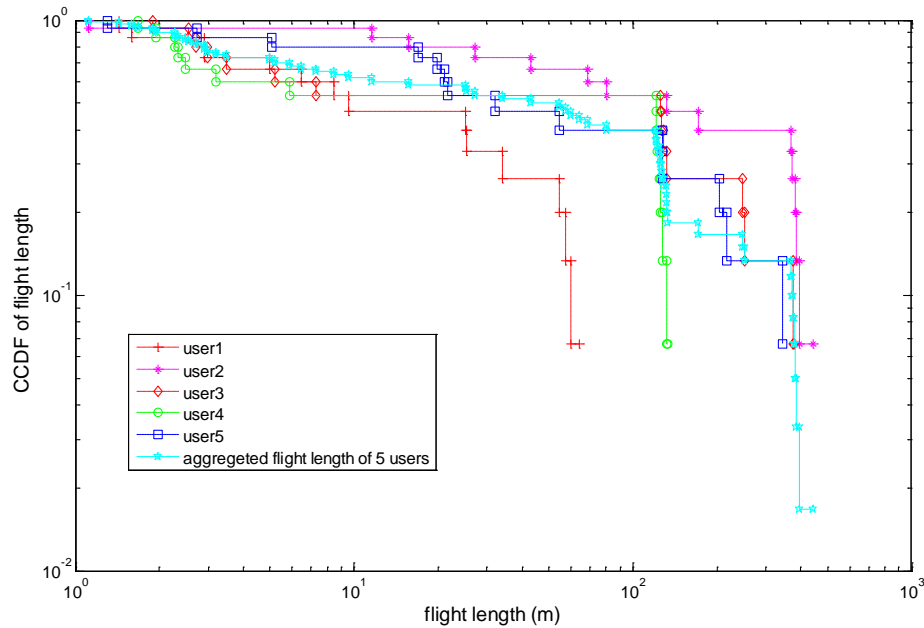
4.2.5 Flight length

Figure 4- 10 CCDF of flight length about 5 different users from 3 groups

Flight length is a characteristic that have not been assigned first in our model, however, the research indicates that the bursty manner spread visit points together with the realistic path planning method can generate truncated power-law distributed flight length values for each user.

To evaluate this parameter, we recorded the flight length of several users in group 1 and group 3 generated by our model. User 1 are randomly selected from group 1, user 4 are selected from group 2, user 2 and 3 from group 3, user 5 from group 4. Simulation time is 48 hours.

The most obvious result that we can find from the figure is that flight length of individual users fits truncated power law distribution. Then we consider the aggregated flight length values of different user from different groups, the result is the same as individual user, which means the flight length fits truncated power- law distribution not only for one user, but also for all users.

Besides, the truncated power law distribution of users' flight length can prove the

invisible boundary's existing in human movement. The infection point appears when the flight length value is close to the maximum side length of simulation area, which is also the truncated point of preferred area's radius.

The similarity between user 2,3 and 5 shows us that the flight length is not related to the density of users' in a simulation area. In group 3, the users are distributed in 800m*800m area sparsely, but in group 4, the users are dispersed in the area with same size densely. However, no matter how many users are there in the simulation area, the flight length distribution turn out to be the same for randomly selected user 2,3,and 5.

Then we aggregated the flight length values together to analyze the statistic performance of all users' displacement. The conclusion remains the same. Our mobility model can ensure that the flight length generated during simulation fits truncated power law distribution, which means the mobility model can represent the characteristic of flight length accurately.
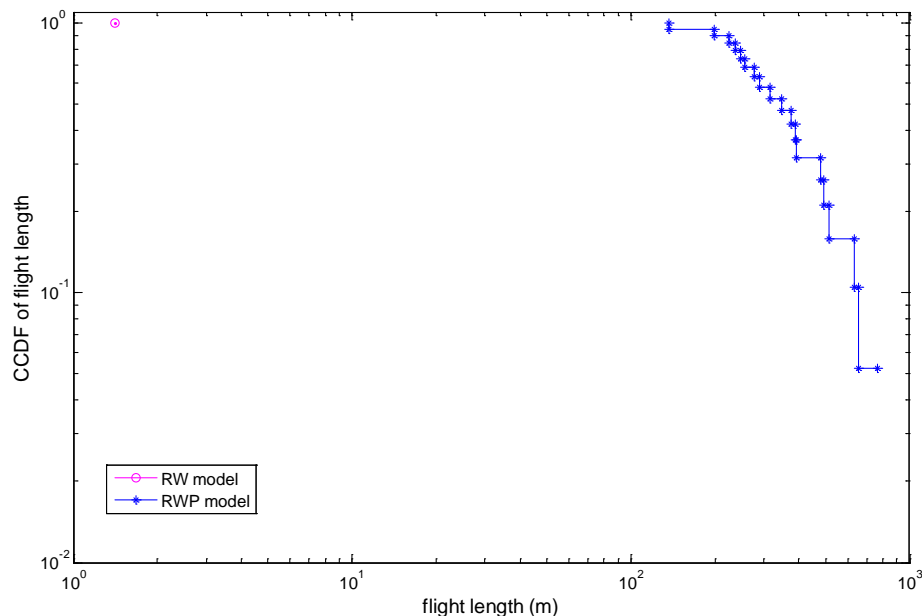

Figure 4- 11 CCDF of flight length (Random Walk model and Random Waypoint model)

We also evaluate the performance of RW and RWP mobility model on this characteristic. The CCDF of RW model is a single point on the figure, which is

obviously not realistic. The CCDF curve of RWP model is similar to the exponential part of real flight length's CCDF, the lack of short range flight length is also not realistic enough.

4.2.6   Velocity

We use the relationship between velocity and flight length to design our model, a new velocity value is assigned to user when the flight length of next trip has been calculated. According to section 2.2.3, we estimate the relationship (Figure 2-2) to 2 straight segments in the log-scale figure. The function of selecting velocity is defined like the Figure 4-8. Since these functions are abstracted from characteristic of human mobility, that means the velocity in our model fits real situation too.
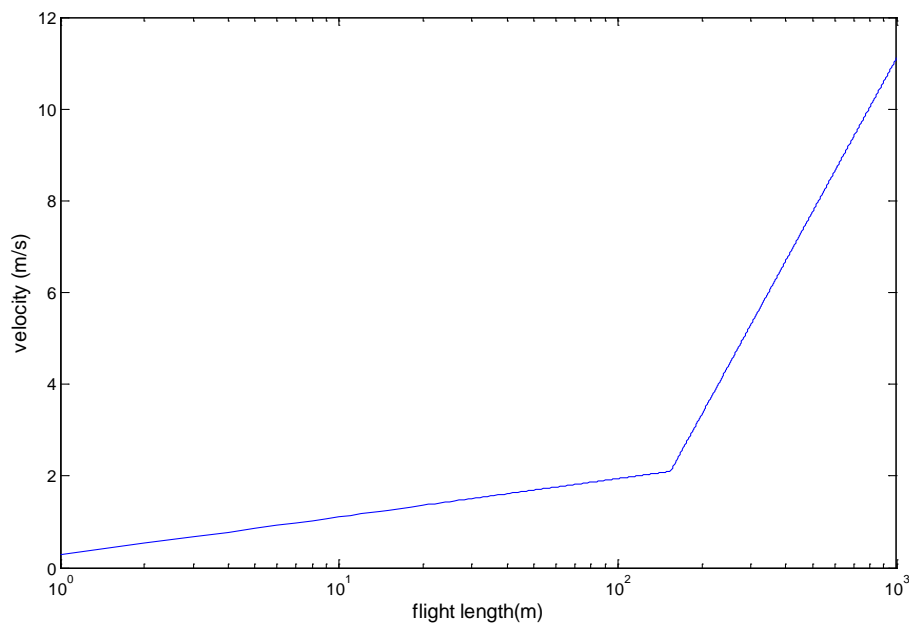
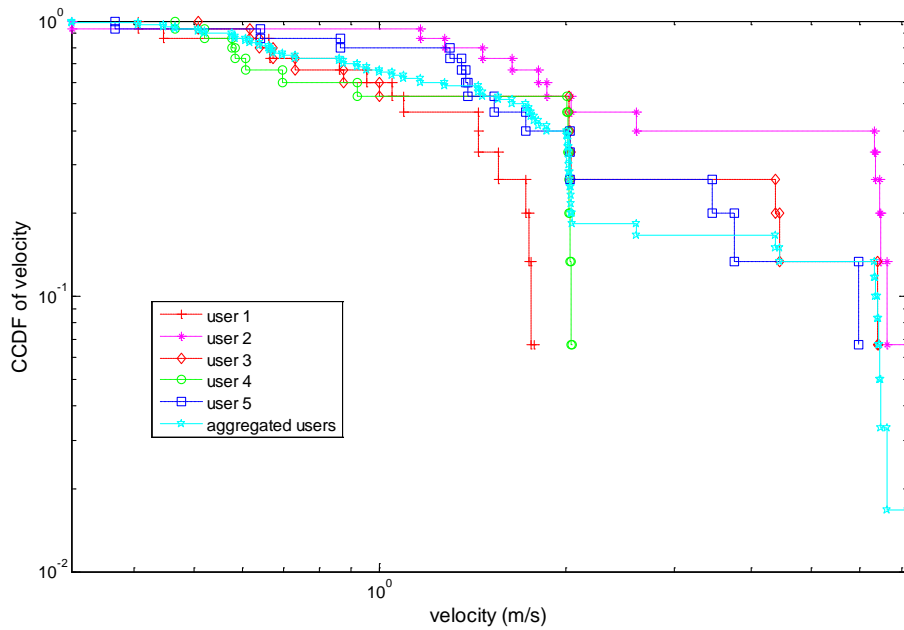Figure 4- 12 The estimation of relation between flight length and velocity

Figure 4- 13 Distribution of velocity of the same users selected in group 3

When we analyze the existing researches, it turns out that the velocity is always a weak point in design of mobility model. But now we can find that the distribution of velocity fits truncated power-law distribution either according to our result. The distribution of flight length has been proved to be realistic, the relation we use to connect flight length and velocity is also realistic, and therefore, the flight length in real movement should have the same result as ours.

We also analyzed the CCDF of velocity in RW and RWP model. Since the velocity are randomly selected from a pre-assigned range $[V_{min}, V_{max}]$, assume $V_{min} = 0, V_{max} = 5$ as an example, the velocity of both model follows uniform distribution.
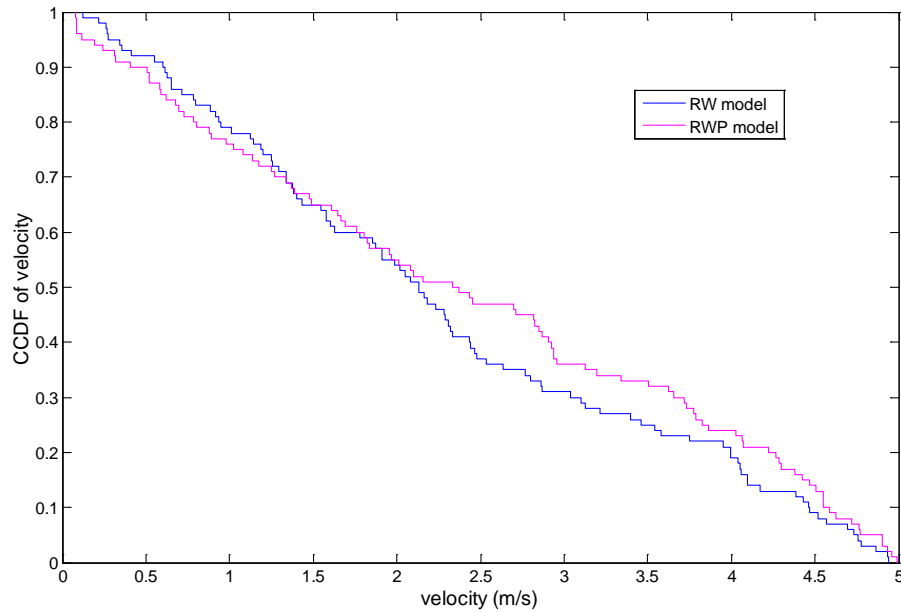
Figure 4- 14 CCDF of velocity (Random Walk model and Random Waypoint model)

4.3 Contribution

	RW	RWP	RD	SLAW	Our model
C1 (Pause time)	×	×	×	√	√
C2 (Return time)	×	×	×	√	√
C3 (Velocity)	×	×	×	×	√
C4 (Angle change)	×	×	×	×	×
C5 (Flight length)	×	×	×	√	√
C6 (Preferred area)	×	×	×	×	√

Table 4- 2 Performance of 5 mobility models.

×: the performance of this characteristic is not realistic

√: the performance of this characteristic is realistic

We have discussed the disadvantages of existing mobility models thoroughly in Section 2.3. Therefore we will not compare our mobility model with all other models. We only list a table here to show us the performance of 3 old models, 1 realistic model and our new build mobility model.

As for Random walk mobility model, Random waypoint mobility model, Random direction mobility model, they could be useful to represent purely random movement, but when the evaluation comes to characteristics of human mobility, none of them can represent any characteristics accurately.

Then we compare our model with SLAW, which is recognized as a realistic model.

SLAW considered pause time, return time, flight length and represent them in a realistic way. However, there are 2 aspects which cannot be ignored from daily experience, velocity and preferred area. But in our model, these 2 aspects have been considered thoroughly and also been represented accurately.

To conclude, after performance analysis, the results show us that our mobility model can fit 5 characteristics:

- *C1 (Pause time):*
    - Pause time of our model fits truncated power law distribution
- *C2 (Return time):*
    - Users can be found in their initial positions after every 24 hours
- *C3 (Velocity):*
    - Velocity is selected according to the flight length
- *C5 (Flight length):*
    - Flight length of our model fits truncated power law distribution
- *C6 (Radius of preferred area):*
    - The re-calculated radius of preferred area fits truncated power law distribution

The performance of these 5 characteristics in Section 4.2 indicates that our model is realistic. By using our model, the human mobility can be represented accurately; the model can be used in many other areas to support the related research.

5 Conclusions

5.1 Conclusions

Movement of network nodes is essential for the performance improvement of wireless network. A mobility model which can accurately capture the movement behavior of nodes or users is needed.

Many models have been built for this purpose, but there are still some disadvantages in them and some aspects have not been considered. Since the mobility model is used to represent real movement of nodes or users, the characteristics of human mobility are extremely important. As we have discussed in section 2.2, there are 6 main characteristics of human movement, pause time, return time, velocity, direction, displacement and preferred area. All these characteristics are the goals of mobility model designing. However, the existing mobility models cannot fit these characteristics. Some of them only represent the randomness of movement, i.e. random walk mobility model, random waypoint mobility model, random direction mobility model. As for other existing mobility models, although they have considered some particular characteristics, but since none of them have analyzed and abstracted all these characteristics before the design, the models turn out to be only realistic in 3 aspects at most.

In this thesis, we present a new mobility model which can capture 5 characteristics of human mobility that we have concluded from existing research.

The foundation of this model is that we admit the existence of invisible boundary in human movement. By using the definition of preferred area's radius, we set up our mobility model.

Another basement of this model is the self-similar distribution of aggregated visit points and individual user's visit points. They both have an uneven spread pattern.

Based on these aspects, our mobility model is designed which can represent human mobility in a realistic pattern.

The proposed model has been evaluated through simulation. The simulation contains various scenarios, we analyzed the performance of this mobility model and compare the statistic performance with the characteristics of human mobility which have been specified in section 2.2. The result turns out to be better than other existing models. 5 characteristics have been represented accurately. Therefore, our mobility model is able to be used in network analysis, protocol design, resource allocated and many other areas.

5.2   Limitations and Future work

In this thesis, our mobility model provides some unique contributions and performance improvements over the existing models. However, the study still has some limitations, which are summarized below:

The lack of real data of human movement records could be a disadvantage of this study. We can only analyze the figures in existing papers.

In the future, if we can record human traces by ourselves, we can evaluate and compare more scenarios of human mobility. For example, human movement in one floor or room. The mobility model based on this kind of short-range scenario could be more useful in 60GHz or personal network.

As we concluded in Section 2.2, there are 6 main characteristics of human mobility. Our model can represent 5 of them accurately, but the characteristic of angle change during movement has not been satisfied. In future, the performance of our mobility model could be improved if we can also represent direction angle change in a realistic way.

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Figures and Tables

List of Abbreviation

MN	Mobile Node
RW	Random Walk
RWM	Random Walk Model
RWP	Random Waypoint
RWPM	Random Waypoint Mobility Model
RD	Random Direction
MRP	Markovian Random Path
SIMM	Simple Individual Markovian Mobility model
LATP	Least Action Trip Plan
SLAW	Self-similar Least Action Walk
CCDF	Complementary Cumulative Distribution Function
PDF	Probability Density Function
EPDF	Equal-Error Probability Density Function
ICT	Inter-contact Time