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ANALYSIS OF USER MOBILITY MODELS BASED ON OUTDOOR MEASUREMENT DATA AND LITERATURE SURVEYS

Master of Science Thesis

Examiner(s): Associate Professor
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ABSTRACT

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The main objectives of the presented work are to study the various existing human mobility models based on literature reviews and to select an appropriate and simplified mobility model fit to the available measurement data. This thesis work is mainly processing a part of "Big Data" that was collected from large number of people, known as Mobile Data Challenge (MDC). MDC is large scale data collection from Smartphone based research.

The thesis also addressed the fact that appropriate mobility models could be utilized in many important practical applications, such as in public health care units, for elderly care and monitoring, to improve the localization algorithms, in cellular communications networks to avoid traffic congestion, for designing of such systems that can predict prior users location, in economic forecasting, for public transportation systems and for developing social mobile applications.

Basically, mobility models indicate the movement patterns of users and how their position, velocity and acceleration vary with respect to time. Such models can be widely used in the investigation of advanced communication and navigation techniques. These human mobility models are normally classified into two main models, namely; entity mobility models and group mobility models. The presented work focuses on the entity mobility models.

The analysis was done in Matlab, based on the measurement data available in MDC database, the several parameters of Global Positioning System (GPS) data were extracted, such as time, latitude, longitude, altitude, speed, horizontal accuracy, horizontal Dilution of Precision (DOP), vertical accuracy, vertical DOP, speed accuracy etc. Parts of these parameters, namely the time, latitude, longitude, altitude and speed were further investigated in the context of basic random walk mobility model.

The data extracted from the measurements was compared with the 2-D random walk mobility model. The main findings of the thesis are that the random walk model is not a perfect fit for the available user measurement data, but can be used as a starting point in analyzing the user mobility models.

PREFACE

This Master of Science thesis work, "Analysis of User Mobility Models Based on Outdoor Measurement Data and Literature Surveys" has been written to complete my M.Sc. degree in Department of Electronics and Communication and Department of Automation Science and Engineering at Tampere University of Technology (TUT), Tampere, Finland.

Firstly, I would like to pay my deepest gratitude to my mentor and supervisor, Associate Professor Elena Simona Lohan, for not only introducing me for this research topic but also for her kind attitude, long term support and immense guidance throughout my thesis work. It could not have been done without her supervision, advice and attention towards my work. Secondly, I would like to express my deep appreciation to my second supervisor, Professor Robert Piche for providing me an opportunity to work in the diversified and vivacious Positioning and Algorithms group and also for examining my work. I am also thankful to Helena Leppäkoski for providing me positive feedback and motivation during my work.

I would like to pay my deepest gratitude to my family especially my parents whose kindness, care, continuous support, encouragement and ultimate love to complete my studies. I am proud to say that whatever I have achieved is because of them.

Finally, I would also like to thank all my friends in Finland and Pakistan for their encouragement and moral support, especially Waqas Khan, Ali Hassan and Sidy Diabate for their constant encouragement and support during the completion of my thesis work.

I would like to dedicate my thesis work to my parents.

Tampere, November, 2014
Shahbaz Baloch

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LIST OF SYMBOLS AND ABBREVATIONS

2D	Two Dimensions
3D	Three Dimensions
MN	Mobile Node
GPS	Assisted GPS
AGPS	Assisted GPS
DOP	Dilution of Precision
RWM	Random Walk Model
CTRW	Continuous Time Random Walk
PCS	Personal Communication System
HHW	Heterogeneous Human Walk Model
TLF	Truncated Levy Flight
MANET	Mobile Ad Hoc Network
VANETS	Vehicular Ad Hoc Networks
AP	Access Point
MDC	Mobile Data Challenge
KL	Kullback Leibler
RSS	Received Signal Strength
TDoA	Time Difference of Arrival
TOA	Time of Arrival
RTT	Round Trip Time
AOA	Angle of Arrival
ITS	Intelligent Transportation System
LDCC	Lausanne Data Collection Campaign
WSN	Wireless Sensor Networks
NLOS	On-Line-of-Site
BS	Base Station
MS	Mobile Station
GNSS	Global Navigation Satellite System
AGNSS	Assisted GNSS
WLAN	Wireless Local Area Network
Ads	Advertisements
S_n	New Speed of a Mobile Node
d_n	New Direction of a Mobile Node
P	Probability Density Function
Δr	Jump Size

r_g	Radius of Gyration
Δt_f	Flight Time
Δt_p	Pause Time
$f(\Delta x)$	Spatial Displacement
$\phi(\Delta t)$	Temporal Increment

1. INTRODUCTION

This chapter is dealing with the current status of research about the human mobility modelling, thesis work motivation and also the author's contribution to this thesis. This is also important to mention that this thesis work is processing a part of "Big Data" that was collected from large number of people, known as Mobile Data Challenge ("MDC"). MDC is large scale data collection from Smartphone based research [8].

1.1 State of art

The problem of modelling human mobility has been studied during the last decade. Nowadays, many research groups are trying to address this problem.
In 2005, the author P. Hui in [1] outlined the specific impact of community by analyzing it from mobility traces.

In 2008, Gonzalez et al., in [2] also utilized this approach by studying a data collected from different mobile phone users whose positions were recorded for several months in order to understand the basic laws governing the human mobility. Similarly, in 2008, Zhao et al., in [3] explained the fact that the human mobility is governed by the power law in both spatial and temporal domains.

In 2010, Song et al., in [4] argued about the existence of Continuous Time Random Walk (CTRW), meaning that human mobility is in its essence random. The authors supported the fact by employing empirical data on human mobility to characterized CTRW models. During the same year 2010, Kiukkonen et al., in [5] described a data collection campaign and mentioned about mobile software for data collection which assist various aspects of human movements.

During the year 2011, Karamshuk et al., in [6] highlighted this topic by portraying about the nature of human mobility along 3 dimensions; spatial, temporal & social. The authors discussed the shortcomings of current models of human movement. However, during the same year 2011, Rehee et al., in [7], contradicted the random nature of human movements.

More recently, in 2012, Laurilain et al., in [8] discussed Mobile Data Challenge (MDC) and also the other mobile related data analysis approaches.

1.2 Thesis work motivation

In a situation where the majority of portable wireless devices are carried by humans, the networking nodes exhibit movement patterns and behaviours of their human carriers and such movement may strongly impacts the network operation and performance. Not only this, but also personalized mobile services could be designed if mobility patterns of each individual were known. The human mobility patterns can be also useful to extract context-aware information needed for enhanced localization approaches (useful especially indoors) and can find their applicability towards solving a variety of social challenges, such as personalized e-health services, reduction in traffic congestion and backbones of smart and green transportation architectures, enhanced personal e-security, and so on-.

1.3 Author contribution

The main author's contributions to the thesis work are given as follows:

1. Literature studies about user mobility dimensions, reviews of various existing entity mobility models and indoor positioning methods.
2. Extracting different parameters from GPS measurement data to utilize them in our basic mobility models in order to know that how best they fit to the basic available models.
3. Developing few algorithms for analysing the available measurement data.
4. Computing the statistics of GPS user data in MATLAB.
5. Analysis of the mobility model parameters in the context of random walk model.

2. USER MOBILITY DIMENSIONS

This chapter will mainly discuss about the classes of human mobility parameters based on three different dimensions, such as spatial, temporal and social dimensions.

2.1 Classification of human mobility parameters

During recent years, the study of the human mobility has been the main focus of different fields of studies and it has opened new topics both in research and development. When talking about human mobility, the research question is about analysing how people visit different locations, whether there are some deterministic patterns of movements and whether there are hidden periodicities in user patterns. The human mobility parameters can be classified based on three dimensions or axes, namely spatial, temporal and social dimensions [6].

1) Spatial dimension: the behaviour of user in the physical space represents the characteristics of spatial dimension (e.g. the users travelled distance).
2) Temporal dimension: the time-varying aspects of human movements describe the characteristics of temporal dimension (e.g. how much time users spend at any specific locations).
3) Social dimension: social characteristics indicate the routine life interaction of users.

Generally, this thesis will discuss all these three dimensions but it will mainly focus on spatial and temporal variations and will ignore the social dimension.

Figure 2.1 shows the classification of human mobility parameters based on three characteristics. In the following Figure 2.1, the spatial dimension represents the radius of gyration and jump size features. In the temporal dimension, it indicates the frequencies of visits, return time, visiting time, user speed distributions and travelled distance distributions features. Lastly, the social dimension depicts the contact time and inter-contact time features.

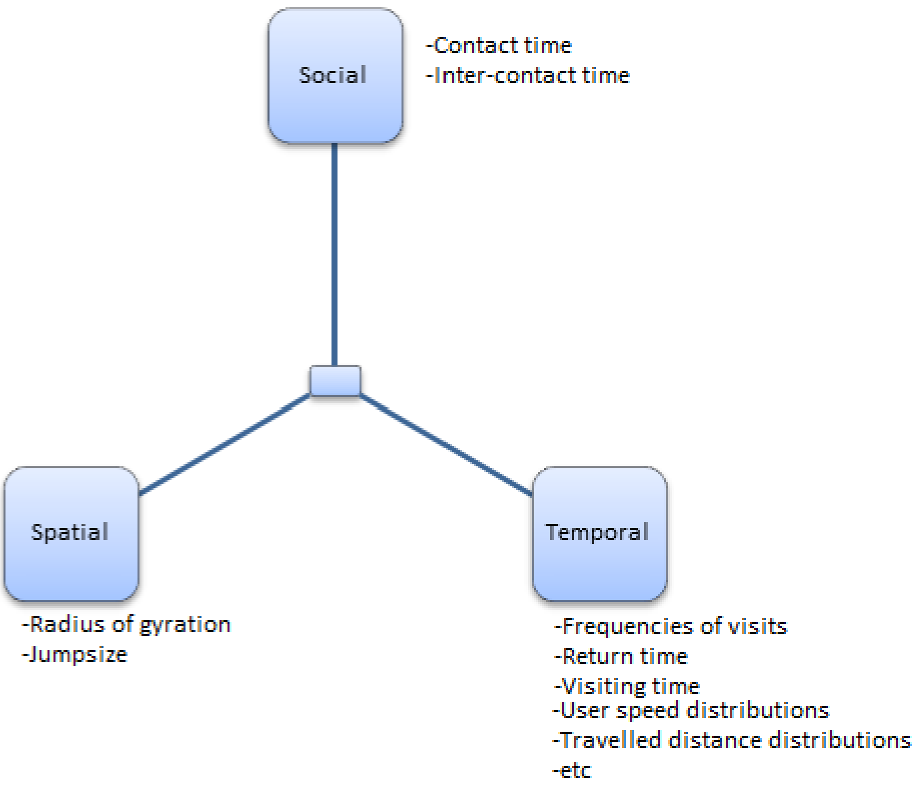

Figure 2.1. Human mobility characteristics

2.2 Spatial dimension

The spatial dimension together with the time dimension, are the most significant characteristics of human mobility. The spatial dimension describes how far a user travels daily from one location to another location. There are various factors which can influence the human mobility including the job requirements, family restrictions and an individual habit of travel etc. [2].

Gonzalez [9] and Brockman [10], approximated human travel distance by a power–law distribution $P(\Delta r) \sim \Delta r^{-(1+\beta)}$

where

- Δr = travel distance is also known as jump size.
- β = is a constant exponent factor smaller than 2.

In [2], the authors tracked 100000 individuals for six months from their mobile phone. Each time user location is updated as he/she received any text message or call with the serving base station's location to reconstruct user time resolved trajectory. Based on these measurements, the authors in [2] approximated the distance travelled by individual in a given time interval by following a power-law probability distribution $P\ (\Delta r)$;

$$P(\Delta r) = (\Delta r + \Delta r_o)^{-\beta} \exp(-\frac{\Delta r}{k}) \qquad (2\text{-}1)$$

where

- P = is probability density function
- β = is a user-dependent exponent, found to vary as β =1.75±0.15 (which is actually mean ± standard deviation)
- Δr_o =1.5 km is a reference parameter
- k= is a cut-off value and it is varying in different experiments and it is user defined.

From equation (2-1), it follows that the human movement can be approximated by Truncated Levy Flight (TLF) [2]. The "Levy flight" named after Paul Levy who is renowned French mathematician. The Levy flight is basically a random walk where the steps are defined in the form of step lengths which have a specific probability distribution in which the directions of the steps is isotropic and random. The authors in [2] explained the variations of $P(\Delta r)$ by three distinct hypotheses:

1) The first hypothesis is that an individual follow Levy flight.
2) The second hypothesis is that the observed distribution has a population-based heterogeneity.
3) The third hypothesis is that both Levy flight and population-based heterogeneity coexist.

These hypotheses have been distinguished by using gyration radius (r_g) which measures the distance travelled by each person. [2], [6]. From the equation (2-1) the distribution of radius of gyration can be approximated with Δr_o can be seen as radius of gyration (r_g) [6]. In [2], it is indicated that, most individuals travelled by a small distance close to their residence while the few others travelled by a long journeys. Moreover [2] suggests that by a Levy flight the individual travel pattern can be approximated up to the gyration radius (r_g) and gyration radius bounds the individual movements.

An important outcome of human mobility model is to find an individual position with the help of probability distribution function of that model. The spatial predictability is usually characterized by centric, orbit and random movements for example, if we consider the movement of an individual amongst few points, then we can imagine a centre point (e.g., home) from where all movements begin and end. Similarly, as in previous example, we can imagine an orbit (such as, from home to college, from college to playground and from playground to back home). Apart from these, there will be some movements that are random and do not follow any pattern, such as going to hospital for treatment due to acute illness.

The spatial dimension can be characterized in terms of direction effect, inter-site distance effect and trip displacement effect [3]. The authors in [3] explain all these effects on the basis of data collected from student daily movement. In [3], the GPS was used to take data every 10 seconds about latitude, longitude and speed of each user. In

[3], the authors collected data for both human spatial and temporal for studying all these effects. Their findings were:

- The direction effect can be thought of as a change of human direction during a trip. They concluded that a human has strong effect of ‘memory’ on direction as a human thinks before moving and already knows the destination point most of the time [3]. Based on the destination point, the change of direction during movement is because of ‘memory’ [3].
- The Inter-site distance effect depends on distance that a user travels. They concluded that the distance travelled by different users follow a power law distribution [3], which states that after a characteristic distance, the distance travelled by a user decreased sharply. The characteristic distance is the distance which varies with a user and depends on user social behaviour/circle.
- The trip displacement effect can be defined as a distance that a user travelled during the movement from its origin. It was observed by the authors in [3] that the trip displacement is actually dependent on different location distances that user visited daily. From collected data, it was observed that the trip displacement was also following a power law distribution. In conclusion, the human trip displacement is actually dominated by a power law distribution of inter-site distance [3].

2.3 Temporal dimension

The temporal characteristics describe the time-varying behaviour of human mobility. For example, such temporal characterization describes how much time is spent at particular location or how many times a location is visited [6]. A temporal dimension can include:

- Frequency of visits
- Return time to a certain place
- Visiting duration

The descriptions of above characteristics can be presented as follows:

1) The frequency of visits can be defined as the number of times a location is visited by particular human. The authors in [2] presented that the tendency of a particular human to visit any location again and again depends on popularity of location as compared to other locations that he/she visits.
2) The return time is the probability to return to a particular location after a specific time. It was concluded in [2] that the prominent peaks at 24 hours or 48 hours

and so on represents the regularly visiting propensity of humans to a location that he/she visited before.

3) The visiting duration describes that how much time human consumes at a particular location. The authors in [4] measured the distribution of a visiting time with the help of large data. It was concluded that the visiting time distribution can be well approximated with truncated power law as expressed previously in equation 2-1 with exponent $\beta = 0.8 \pm 0.1$ and cut-off $\Delta t = 17$ h. Moreover, the authors in [2] found that frequency f_i with which user visited ith most visited location follows Zipf's law ($f_i \sim i^{-\delta}$) with parameter $\delta \approx 1.2 \pm 0.1$. From this it can be concluded that $'f'$ times user visiting probability of a location follows $P(f) \sim f^{-(1+\frac{1}{\delta})}$.

As mentioned in previous section, the real motivation of all models is to predict the human mobility. If it is considered only the spatial distribution, then the human predictability varies a lot and it is insignificant across the whole population [6]. If the factual background of the everyday movement also taken into consideration, then the likely predictability approaches to 93% and it does not vary too much. This indicates that, if the history of a person is known with spatial distribution, then it is possible to anticipate his/her location with better veracity.

The predictability is based on temporal dimension and that it can include periodic, a-periodic and sporadic characteristics:

- Periodic movements represent the occurrence of an event again and again after a particular time on routine basis. For example, if an individual travels to school early in the morning, returns back to home at noon and goes to gym in the evening, the daily axis will represent the periodic temporal behaviour.
- A-periodic can be defined as events that follow random time behaviour. For example, if person visits his/her parents on weekend randomly, then it follows a-periodic temporal behaviour.
- Similarly, sporadic can be defined as events that do not repeat and happen only once. For example, if a person visits any location only once and did not repeat his/her visit during monitoring time, then it follows sporadic temporal.

The temporal dimension has an effect on human mobility in terms of site return time effect and pause time effect [3]. Based on analysis on that data, the authors in [3] explain the site return time effect and the pause time effect.

- The site return time can be explained as the time a user takes to visit any location again. The authors in [3] found that due to human behaviour, the different tasks to perform at different locations and the arrival time to a particular location vary a lot. The authors in [11] observed that human follows diurnal cycle pattern and are expected to return to particular location such as office, home. Based on the study of the site return time at a specific position, the human position can be predicated. Moreover, the authors in [3] observed that some students follow same patterns and visit same location at the same time. Based on this, the inter-meeting time between different students can be predicted. During further analysis, the authors in [3] showed that the site return time followed a "power law exponent ($P(\Delta r) \sim \Delta r^{-(1+\beta)}$)" identical to inter-site distance and the trip displacement.

- The pause time represents the time that a user consumes between two consecutive travels. It was observed that students follow large pause time and short travel time because of human mobility nature and location of visit [3]. Moreover, [3] showed that pause time follows a power law distribution. In conclusion, [3] presented that the site return time and the pause time follows a power law distribution as universal property of human mobility.

The authors in [11] proposed the time-variant community mobility model that considered two important trends of *skewed location visiting preferences* and *periodical re-appearance at the same location* in multiple WLAN traces. The proposed model [11] indicated realistic mobility characteristics. WLAN traces were utilized to understand and to propose a mathematical model of wireless network user (node) [11].

The two important terms *hitting time* and the *meeting time* determines the mobility. The hitting time describes the average time that a node takes moving towards a random location, while the meeting time describes the average time that two nodes takes moving towards each other. Mathematical expressions have been derived for both hitting and meeting times in [11] and verified from simulations. The results in [11] showed the comparison outcomes for both important terms.

In [11] two other important features related to WLAN traces were shown, namely the skew location visiting preferences and the periodical re-appearance at same location. From the study in [11], it is clear that a node consumes greater than 65% of its time to one access point (AP) and after a time span of several integer days node re-appear at the same access point.

2.4 Social dimension

The social characteristics describe how the social relationships influence the choices of locations we normally visit. It also describes the connecting properties between different users. A social dimension can include:

- Contact time
- Inter-contact time

The time in which two users are in contact to each other can be represented as contact time while the time discrepancy among the last and the new contact time between two users can be described as inter-contact time. Chaintreau in [12] shows that the inter-contact time has a power law distribution. Moreover later, Karagiannis in [13] suggests that exponential cut-off should be complemented with a power law distribution. Huiin in [1] shows that contact time also follows an approximate power law distribution.

The social dimension is an important aspect to predict the mobility of an human being. As we spent most of our free time with our friends, family and relatives, it means that understanding or knowledge of these will greatly help to predict the location of human beings. Although we can have meeting with our friends at any location, the knowledge of the three dimensions spatial and temporal significantly improve the accuracy of location prediction [6].The predictability based on social of human mobility can be characterised with meetings, individual jobs and group trips [6].

- **Social meetings** refer to the movements which are based on social contacts, such as when a person moves to meet his or her friend.
- An **individual job** means that the movement is done individual.
- **Group movements** mean that the movement was done by a group of socially connected people.

The understanding of the social structure is very important in order to model the pragmatic social dimensions of human movements [14]. The authors in [14] proposed a heterogeneous human walk model (HHW) that explains this characteristic from real traces. The social network theory [15] is a powerful and useful mathematical tool to explain the complex social relationships between people. It has been observed that a community (which is composed of set of individuals) structure has a huge impact on people motion. For example, the people from the same society see each other more often than the people from other societies [14]. The social network, which is actually the interaction between the individuals, can be represented in undirected graphs [15]. Figure 2.5 shows the social network of individuals. Part (a) of figure shows the general social architecture, part (b) shows the independent society architecture while part (c) shows the over lapping community structure where individuals from different community interact with each other [14].

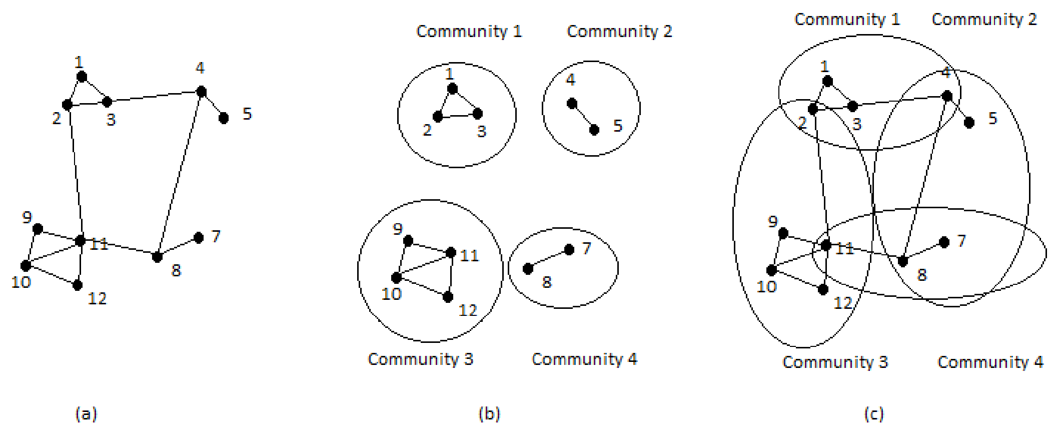

Figure 2.2. (a) Represents social architecture (b) Represents independent society architecture (c) Represents over lapping community architecture (reproduced from [14])

The authors in [14] suggest that the mobility models can be divided into two classes, namely the real-trace-based models and the social-aware models.

- The real-trace-based models are made on real trace results obtained from GPS, WLAN or some other means. These models consider each node independent to other and do not take into consideration the social interaction among nodes. This means that, reality of these models is not clear in the social network environment [14].
- The social-aware models can be divided into two sub-models, namely the community-based model and the sociological behaviour-based models. The community-based model uses a social network while the sociological behaviour-based models use some sociological research results [14]. Neither of these models considers the heterogeneous human popularity and also requires manual input of social graphs [14].

The authors in [14] proposed HHW model which comprises of three parts:

- Overlying society and hybrid establishment
- Community alignment to geographical location
- Individual motion extraction

The following example explains how different people from the different social network have different periodically time-varying social behaviour in the society [14]. Figure 2.3 shows scientist X1's social behaviour throughout the day. From Figure 2.3, it is clear that scientist's day starts with family, then act as teacher, after this spends time with researcher and in the evening time will be spent with friends. In each community, scientists have different people as well as there is not interaction of the different community people [14].

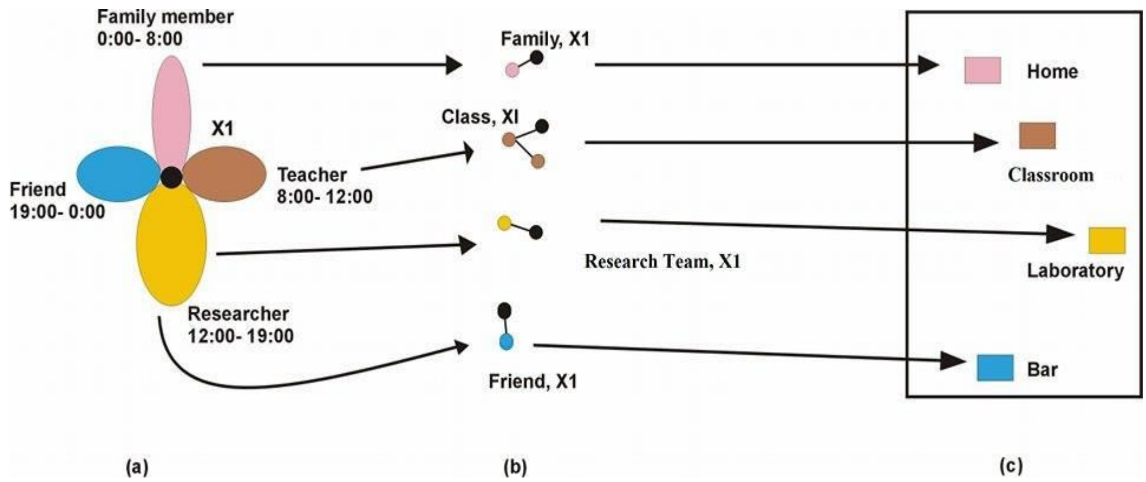

Figure 2.3. (a) Scientists X1 at different time of day (b) X1's community in each period of day (c) Community location (reproduced form [14])

Figure 2.4 shows X2 salesman's behaviour throughout the day. It can be observed that behaviour of salesman is global and the different community's people have interaction with each other as compare to scientist's behaviour [14].

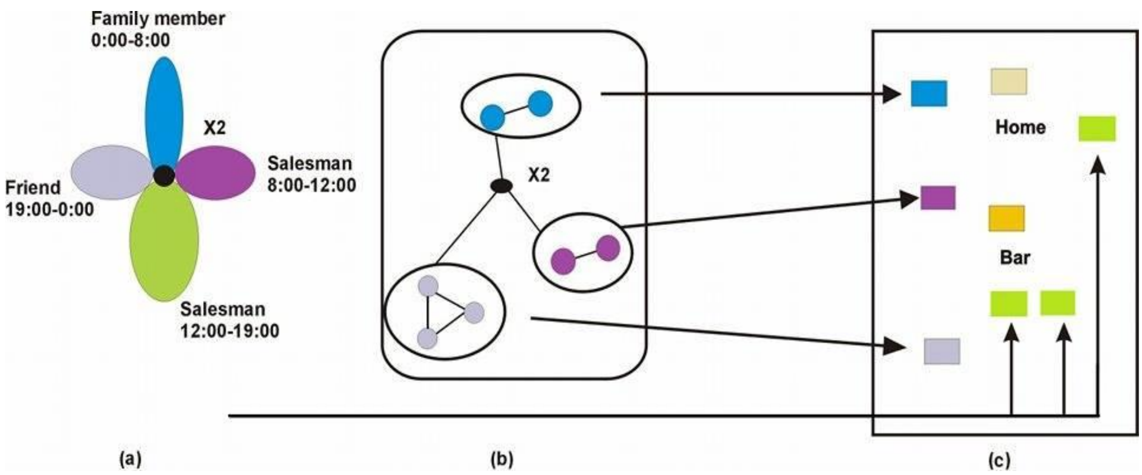

Figure 2.4. (a) Salesman X2 at different time of day (b) X2's community in each period of day(c) Community location (reproduced from [14])

The authors in [16] propose the working day movement model which is combination of different designs, known as submodels. Based on study done in [16], any node has ability to perform following three activities:

- Staying at home
- Staying at work place
- Performing activities with buddies in the evening

There can be some other activities but according to the authors in [16], most of the day can be covered with above mentioned activities. It is suggested that to fine tune the parameters and to get more accuracy further sub-models can be added [16]. The Figure 2.5 shows different sub models highlighted in [16]. Details of each can be found in [16].

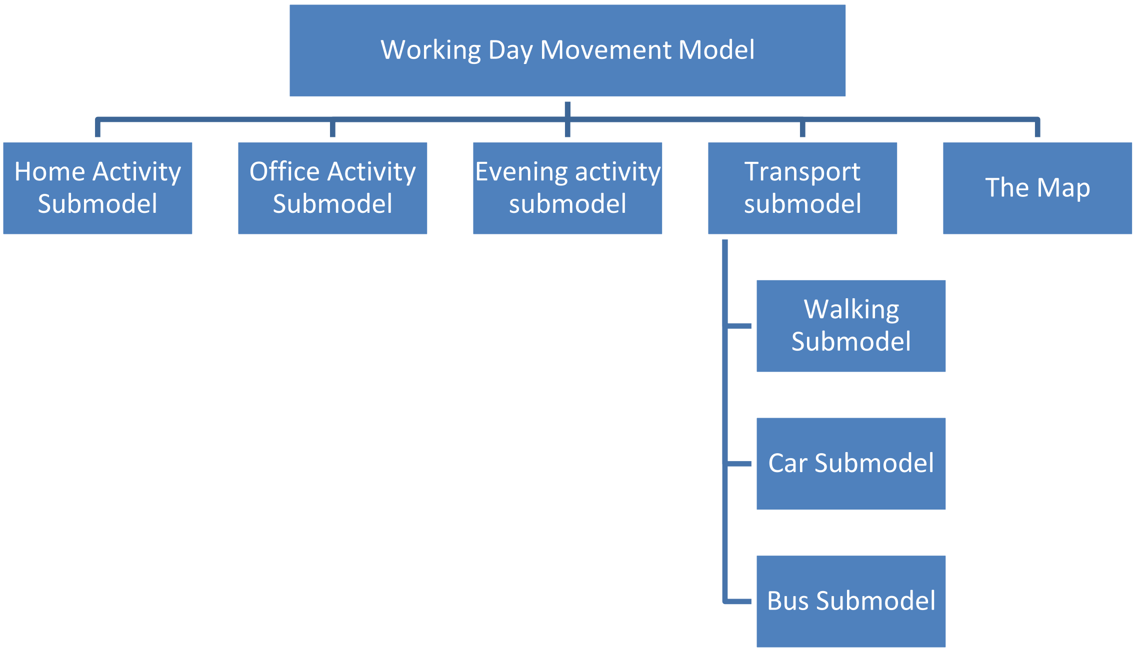

Figure 2.5. Working day movement model and its submodels

At the end of this chapter, one important aspect of mobility needed to be highlighted as well as the scale of mobility [6]. It can be separated into three levels:

- Building/area wide
- Village or City wide
- Global

Apparently, the scale parameter looks only to spatial scale, but actually it also contains the other temporal and social scales as well. For example, if we consider building/area wide movement, then the travel time will be small and our stay at any location will also be small. Moreover, we interact with people of that small building/area community. If we travel outside of the city, then our stay will be likely long and our interaction will be likely with a large number of people. Similarly, if we travel to other country, then we will prefer to stay for a longer time and our interaction will probably (though not necessarily) be with a much larger number of people than in a home building [6]. It means that all these aspects are also important while modelling human mobility or predicting the location of human.

3. USER MOBILITY MODELS

This chapter will introduce various existing mobility patterns which are related to different categories. The main focus in this thesis will be on random walk model as this is the simplest one to implement.

3.1 Human mobility modelling

As emphasized so far, the human mobility modelling is one of the demanding and challenging tasks these days and many researchers worldwide are interested in the movements of a mobile user, namely his or her changes over time in location, velocity and acceleration. For example, one can focus on the user velocity and the frequency of a user in a particular geographical area. The mobility models are commonly used for the statistical analysis or performance evaluations of an ad hoc network protocol and this should be analysed under pragmatic development of the mobile users. Other usages can encompass improved personalized Location Based Services or location-based crime fighting or crime control.

The human mobility patterns can be also useful to extract context-aware information needed for enhanced localization approaches (useful especially indoors) and can find their applicability towards solving a variety of social challenges, such as personalized e-health services, support management of network resources, reduction in traffic congestion and backbones of smart and green transportation architectures, optimization of procedure and protocols , enhanced personal e-security, and so many other practical applications.

3.2 Categories of mobility model

The mobility models can be categories into two major types [17].

- Trace-based mobility models
- Synthetic-based mobility models

The trace-based mobility patterns are those that can be examined in routine life systems and these traces provides precise knowledge especially when they include huge amount of gatherings of people and correspondingly long examination duration. Although, it is difficult to design networks if the traces have not been generated already. In this scenario, it is obligatory to practice synthetic-based mobility models. Additionally, synthetic-based models also describe the behaviour of mobile node realistically even without using the traces [18].

This chapter will describe several existing mobility models that will describe the behaviour of mobile users with respect to their movements either they are dependent or independent from each other. Mainly, these two types are as follows:

- Synthetic entity mobility models
- Group mobility models

In the first category of models, nodes are independent in movement from one another. The second category follows the movements of nodes in group.

But this thesis work will focus on synthetic entity mobility models. Basically, the main aim of presenting several mobility models is to offer more informed and realistic choices to researchers while deciding upon the movement pattern for the performance evaluations of an ad hoc network. Figure 3.1 shows the different classifications of mobility models.

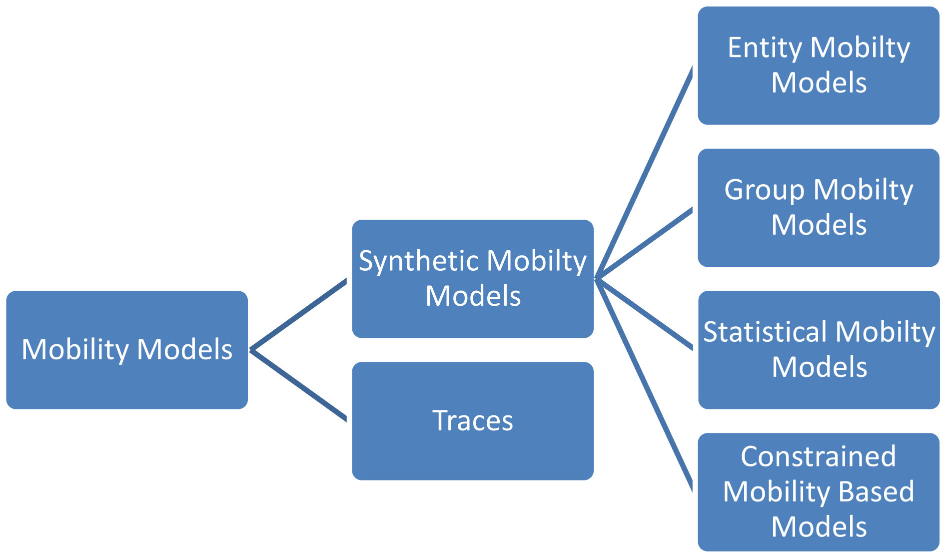

Figure 3.1. Categories of mobility models

3.3 Synthetic mobility models

As it is mentioned above, the main focus of this thesis is on the synthetic entity mobility patterns. These patterns are the one in which nodes are not dependent on each other during their movement. It will be discussed here several existing synthetic entity mobility models in the current literature.

3.3.1 Random walk mobility model

This mobility model is very common in use and also developed on large scale, it is referred to as Brownian walk [19]. It was introduced mathematically by Einstein for the very first time in 1926 [20]. This model is usually considered as a starting point for all other existing mobility models. It is based on random speeds and directions. There are a lot of items or individuals in our surroundings, those moves in irregular patterns or unpredicted manners. This type of mobility pattern was introduced to imitate these irregular patterns [18].

In this type of mobility pattern, the nodes or entities move by randomly selecting its direction and velocity from its present position to new position. The mobile node is firstly placed in the simulation boundary and then randomly chooses its direction and speed from the predefined given ranges i.e. $[speedmin, speedmax]$ and $[0, 2\pi]$.

So, every development in random walk model is done either by a traversal time (t) or traversal distance (d) and new direction and speed are calculated at the end and this process is repeated predefined number of times. In this mobility pattern, the following basic parameters are taken into account (the intervals are also specified below)

- $Speed = [speedmin, speedmax]$
- $Angle = [0,2\pi]$
- $Traversal\ time(t) or\ Traversal\ distance\ (d)$, *which are also referred to as the main input parameters (either one or the other is used, not both together).*

The general concept of continuous time random walk (CTRW) is combination of two probability distribution functions, which can be represented by the following formula:

$$(\Delta x, \Delta t) = f(\Delta x)\ \phi(\Delta t) \qquad (3\text{-}1)$$

In equation (3-1), $f(\Delta x)$ describes the spatial displacement, while, $\phi(\Delta t)$ represents for random temporal increment.

After N repetition, the location of the user can be given as:

$$X_N = \sum_{n=1}^{N} \Delta x_n \qquad (3\text{-}2)$$

In above equation (3-2), N is defined for the step number and Δx represents the time increment between successive steps.

The random walk mobility model produces a Brownian motion when it is using with small input parameters (either distance or time), while, it produces the random way point patterns with same input parameters but with large values of these input parameters [18]. In this thesis work, the 2-D random walk mobility model is used for the analysis of available measurement data, due to the lack of time to investigate also the 3-D models.

According to [18], the mobile node chooses its angle randomly among 0 and 2π and also speed among 0 and speedmax= 10 m/s at any point. The scenario of [18], allows the mobile node to move for 60 seconds before changing its direction and speed. In random walk model, the mobile node can also change angle after specific distance instead of time. According to [18], an example where the mobile node changed direction after 10 steps instead of 60 seconds before changing direction and velocity are given.

A random walk model offers both advantages and some disadvantages. The main advantage is that it is the simplest model to implement. Similarly, it generates the unpredicted movement patterns [21]. On the other hand, there are some main disadvantages, such as this model is memory less as it does not hold information related to previous position and velocity, it generates improbable movement patterns such as abrupt pause and acute change [18].

Mainly, this thesis work will generally investigate how far the random walk model is from a realistic model that would fit to user collected data.

3.3.2 Levy walk mobility model

Basically, the Levy walk is a random walk, where the steps are defined in the form of step lengths which have a specific probability distribution, the directions of the steps is isotropic and random. Gonzalez [9] and Brockman [10] approximated the human travel distance by a power–law distribution $P(\Delta r) \sim \Delta r^{-(1+\beta)}$. A truncated Levy flight equation was shown in equation (2-1) [2].

where

- Δr = travel distance is also known as jump size.
- β = is a constant exponent factor smaller than 2.

The authors in [7] constructed the simple truncated Levy flight model and during the analysis of TLF model, the simple random walk model was used. The traces were described by the following four key terms for the step [7].

- $flight\ length\ l$
- $direction\ \theta$
- $flight\ time\ \Delta t_f$
- $pause\ time\ \Delta t_p$

This LTF model randomly chooses the variables (l) and (Δt_p) from their probability distribution functions $p(l)$ and $\varphi(\Delta t_p)$, these are Levy distributions with coefficients α and β, respectively [7].

3.3.3 Random way point mobility model

This model is utilized on a large scale. It resembles to random walk mobility model, however, it includes a pause time between the movements, i.e. development in angle and velocity [22]. The entity initiates the process inside the simulation boundary by randomly choosing position (x, y) as a destination and velocity v which is uniformly distributed between $[minspeed, maxspeed]$ [23].

The entity stays in one position for particular duration (i.e. pause time). When that time expired; the entity inside the simulation area chooses it random destination. Similarly, the entity travels towards a newly selected terminal at specific velocity. So, after its arrival to initiate the development once again, it waits for a particular duration [18].

In this mobility model, the following basic input parameters are considered.

- $Speed \in [minspeed\ , maxspeed]$
- $Destination\ position == [random\_x, random\_y]$
- $Pausetime >= 0$

The random waypoint model has some advantages and disadvantages. The main advantage is that it is normally considered as main building block for developing other mobility models. On the other hand it has some disadvantages, such as it is not good for regular movement modelling, it exhibits density wave(clustering of nodes in the simulation boundary) in the average number of neighbours, it exhibits speed decay (decrease in the average nodal speed) and also it contains memory less movement behaviours, meaning that the personal history information is discarded in this model [21].

3.3.4 Random direction model

There were flaws in the random way point of mobility model, such as speed decay, memory less movement behaviors, density wave and so on- . The random direction model [24] has been introduced to eliminate these shortcomings, such as density wave in the average number of neighbors. A density wave usually means the grouping or clustering of nodes inside any part of the simulation zone. In the scenario of random direction model, the clustering of mobile nodes appears in the center of simulation area. Where as in random direction model, the probability is generally high if the mobile node chooses the new location from the center of simulation boundary. Therefore, the mobile nodes appear to converge, disperse and converge again etc. resulting from changes in the average number of neighbors [18]. To mitigate this type of behavior and counter the number of semi-constant neighbors, random direction model was developed [24].

In this model, the node randomly selected the direction as it does in random waypoint mobility model, then node moves towards the border of simulation area. After reaching at the boundary of simulation area, it stops for a particular duration and starts the development once again by selecting the random direction among (0 and π) and keep going the development again. The following input parameters are used in this model.

- $Speed \in [minspeed, maxspeed]$
- $Direction \in [0, \pi](initial[0,2\pi])$
- $Pause\ time$

The minor variation in this mobility model produces the modified random direction mobility model. Due to this modification, the node selects random directions but it is no longer obligated that for changing a direction, the node travel to the boundary of simulation before stopping. In this way, the node chooses random direction and selects the final terminal where ever it wishes to travel.

This model has some advantages and disadvantages. The main advantage is that, this model eliminates the density wave and it exhibits uniform distribution of chosen routes [21]. On the other hand, it has some disadvantages, such as, it exhibits unrealistic movement patterns and average distances among the nodes are greater than the other movement patterns [21].

3.3.5 Weighted way point mobility model

In the previous work of existing mobility models one of the important aspects was not addressed, i.e. the destination is not purely chosen random for the pedestrian. It has been noticed that people usually visit more familiar locations than visiting other random locations. So, a new model was introduced called weighted waypoint mobility model. In this type of mobility model, the parameters are time and position dependent.In [25], the parameters of this model through survey data for campus mobility were calculated and compared with the results of the survey with information from wireless network traces.

According to [25], an example was developed for this model based on a mobility survey which was conducted in the campus area. By utilizing this example as an input to a simulated ad hoc network, it has been shown that the preferences in choosing destinations tend to lead to a significant deterioration of the performance of an ad hoc routing protocol.

However, the different characteristics between this model and popular random waypoint mobility models are as follows [25].

- A mobile node no longer choose random directions; In routine life it is unusual for a person to choose random location towards his/her destinations, such behaviour was modelled by defining the familiar locations in the simulation area and assigned various ”weights” depending on the probability of selecting destinations from the area [25].
- At every point the pause time distribution is distinct and it is a property of that position [25].

The weighted waypoint mobility model offers some inconsistencies, such as: in this model mobile node exhibits uneven (clustering or grouping) and time-varying spatial distributions. Moreover, it minimizes the achievement rate of route detection because the clustering effect causes greater congestion in wireless lane network [25].

3.3.6 A boundless simulation area mobility model

It is observed widely in other mobility models that mobile nodes exhibits off or stop moving phenomena once they hit the boundary of simulation. In the boundless simulation area mobility model, mobile node does not stop at the boundary but keep going from one perimeter to another opposite one without even being stopped.

Figure 3.2 illustrates the travel pattern of mobile node by using boundless simulation in 2-D scenario with N=200 steps of movement, maximal speed is Vmax= 1.4 m/s and angle limitation is between ($-\pi$ and π). When the mobile node arrived at perimeter, it can be represented by cross in the figure, while, a circle represents the return of it.

This model shows the accordance of mobile nodes among the past travel direction and speed with the present travelling direction and speed [26]. In this mobility model, it is observed that in order to represent the velocity ($\boldsymbol{v}$) and direction (ϴ) of mobile nodes the velocity vector is deployed, while, (x, y) specified the position. So, both these factors of mobile nodes can be notified on each Δt time steps based on the parameters described below [18].

$$v(t+\Delta t) \in \min\{\max[v(t)+\Delta v, 0], v_{max}\} \quad (3\text{-}3)$$
$$\theta(t+\Delta t) = \theta(t)+\Delta\theta \quad (3\text{-}4)$$
$$x(t+\Delta t) = x(t)+v(t) * \cos\theta\,(t) \quad (3\text{-}5)$$
$$y(t+\Delta t) = y(t)+v(t) * \sin\theta\,(t) \quad (3\text{-}6)$$
$$\Delta v \in [-A_{max} * \Delta t, A_{max} * \Delta t] \quad (3\text{-}7)$$
$$\Delta\theta \in [-\alpha * \Delta t, \alpha * \Delta t] \quad (3\text{-}9)$$

where

- v_{max} = maximal speed.
- $v(t)$, $\theta(t)$ = describes the velocity and direction of mobile node, respectively.
- $x(t)$, $y(t)$ = both represent the positions of mobile node.
- $\boldsymbol{\Delta v}$ = variation in speed in $\Delta t\ time$.
- A_{max} = the maximum defined acceleration of a given mobile node.
- $\Delta\theta$ = variation in angle and α represents the maximal angular change in direction of mobile node.

A boundless simulation area mobility model has several advantages but the main advantage is that this model permits the mobile nodes to move other side of the simulation area without being stopped when they encounter a border unlike all other existing mobility models [27]. But this model is not suitable for the human mobility model.

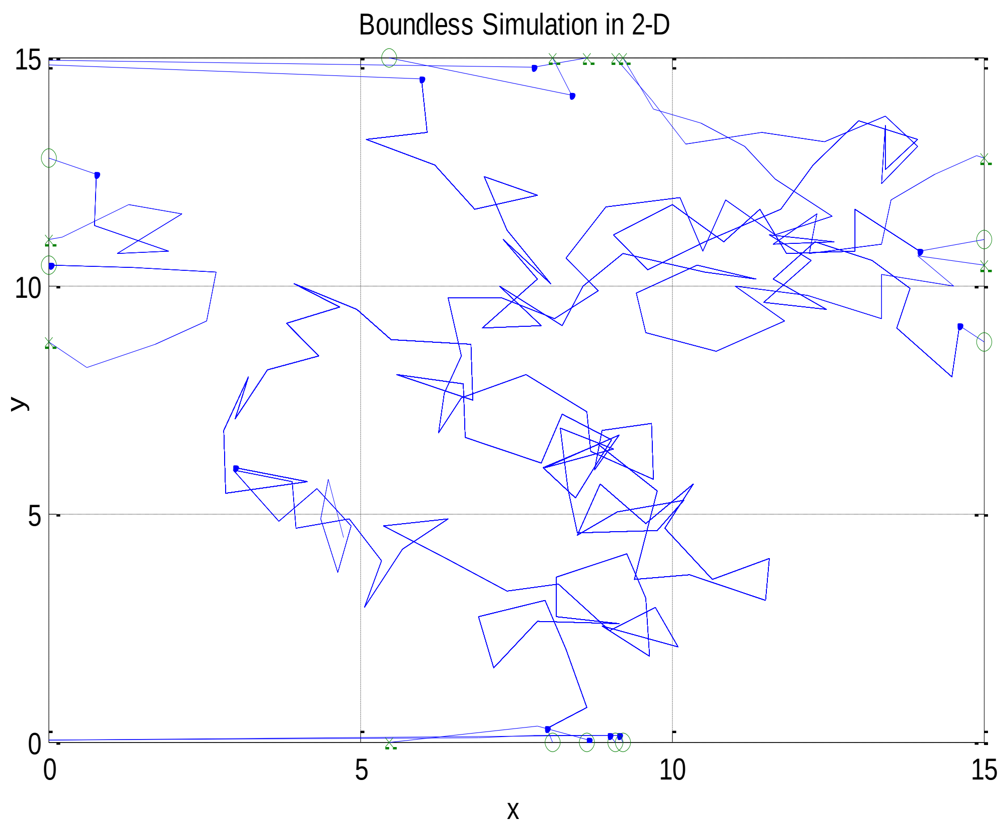

Figure 3.2. Movement pattern of mobile node in 2-D boundless concept

3.3.7 The Gauss-Markov mobility model

This model has been developed and used for simulation purposes of both the personal communication system (PCS) and an ad hoc network protocol. This model was designed using one parameter to specify the various levels of randomness.

In the beginning, each mobile node is assigned a current speed and direction. The new speed and direction of each mobile node is being updated after 'n' movements at fixed interval of time. Moreover, the value of speed and direction is being calculated at the n^{th} instance depending on the values at $(n-1)^{th}$ instance and based upon on the random variables using the following parameters [18].

$$s_n = \alpha s_{n-1} + (1-\alpha)\bar{s} + \sqrt{(1-\alpha^2)} s_{x_{n-1}} \tag{3-10}$$

$$d_n = \alpha d_{n-1} + (1-\alpha)\bar{d} + \sqrt{(1-\alpha^2)} d_{x_{n-1}} \tag{3-11}$$

where

- $(s_n\ ,\ d_n)$ = represents the mobile nodes new velocity and direction, respectively.

- α = represents tuning parameter, its range is between $0 \leq \alpha \leq 1$.
- $(\bar{s}, \bar{d})$ = are the constant values.
- $s_{x_{n-1}}$, $d_{x_{n-1}}$ = describes the random variables from a Gaussian distribution, respectively.

It also has been observed that varying the tuning parameter exhibits different behaviours of randomness. By adjusting the value of $(\alpha = 0)$ the random values or Brownian values can be obtained while changing the value of $(\alpha = 1)$ the linear motion can be obtained and similarly, intermediate values of randomness can be obtained by adjusting the values of (α)between 0 and 1.

As we mentioned above that a mobile node next location, speed and direction are estimated depending on present position. So, the mobile node position can be located from the following parameters [18].

$$x_n = x_{n-1} + s_{n-1}\cos d_{n-1} \quad (3\text{-}12)$$
$$y_n = y_{n-1} + s_{n-1}\sin d_{n-1} \quad (3\text{-}13)$$

where

- (x_n, y_n), (x_{n-1}, y_{n-1}) = represents the position coordinates of the mobile node at time intervals n^{th} and $(n-1)^{th}$ respectively.
- (s_{n-1}, d_{n-1}) = represents mobile node velocity and angle at time interval $(n -$ val $(n-1)^{th}$.

The Gauss-Markov mobility model offers several advantages. For example, it eradicates the abrupt pause and acute change observed in the random walk model, permitting the previous speed and angles to influences forthcoming speed and angles.

3.3.8 The city section mobility model

The city section mobility model has been designed to provide realistic movements of mobile node with a restricted behaviour for a small section or street of a city and it was first proposed by Davies [28]. In this scenario, the mobile nodes need to obey the already defined routes and guidelines e.g. traffic rules and regulations. In real scenario, it is rare for the mobile nodes to move freely because they don’t have tendency to disobey the obstacles and traffic rules.

Moreover, the people adopt to move in similar patterns during walk around their surroundings or driving towards downtown. The average hop count in simulations will be increased in result of restricting all mobile nodes to obey the predefined paths in case of comparing this model with other existing mobility models.

In the simulation boundary, mobile node initiates the process by already described mark on any avenue, after that mobile node selects the destination at random that is indicated by mark on any avenue. Moreover, a movement path is located between starting point to ending point in a shortest travel of time among two marks and also driving safety properties let say speed restrictions and shortest distance permitted among two existing mobile nodes. Once the mobile node approaches the destination, then it is stopped for a particular duration, after that chooses another random destination on any point of the avenue and then repeats the development.

Although, this model has several advantages but it needs further developments such as, it required to utilize maps of the city. Moreover, this model needs to be developed further in order to maximize the simulation field, introduce maximum number of routes and also developed fast acceleration routes with the perimeter of simulation field [18].

3.3.9 Traffic simulator based models

The researchers and some companies have provided the approaches for studying the realistic traffic simulators based on real traces and behavior surveys. These models are developed for the transportation planning, fine grain simulators for example, PARAMICS [29], CORSIM [30], VISSIM [31], TRANSIM [32] and SUMO [33], these are used for modelling the city transport planning at both small and large scales, power utilization and also for infection control. These models are not useful in network simulators because there is no infrastructure still available for their development and also these are used in commercial scales so there is need of purchasing license. Moreover, the major disadvantage of these traffic simulators is the configuration complexity.

The traffic generator is one of the main considerable building blocks for generating vehicles and modeling their mobility while maintaining the regulations introduced by the motion constraints. So, for vehicles mobility modeling the following building blocks of traffic generator are important;

- **Trip generation:** trip is either randomly generated or sometimes by setting according to the sequence of activities. This trip is generated between source and destination even without being considering the time patterns and either interaction among past and forthcoming locations.
- **Route estimation:** route estimation facilitates the methods that help to develop an entire route among starting and final locations during the way to trip constructed by the trip generator.
- **Human movement patterns:** In this type of traffic generator, the human movements inside the vehicle and its interactions with the other vehicles are characterized accordance to analytical models, for example, the car flowing and behavioral model etc. According to Brackstone [34] the car flowing models can be classified into five categories which can be studied in references cited in [34].
- **Lane changing models**: lane changing models describe the overtaking phenomena in road safety and it also has some other models which can also be studied in references cited in [34].

4. DATA GATHERING ISSUES

This chapter deals with the data gathering issues. This is also processing a part of “Big Data” that was collected from large number of people known as Mobile Data Challenge (“MDC”). MDC is large scale data collection from Smartphone based research [8]. Firstly, the different methods used to protect the privacy of consumer are presented. Afterwards, there is discussion about what type of ethical issues and potential threats arise when dealing with the data gathering. At the end, there is explanation of different technologies available to gather the data.

4.1 User privacy issues

The privacy of user data has prime importance while collecting any data related to user private life. Therefore, the necessary measures should be taken to satisfy the ethical and legal requirements. The authors in [8] summarized the data privacy approach in four different steps:

1) Inform volunteer about privacy sharing.
2) Security of data.
3) Anonymization of data.
4) Inform researcher about privacy respect.

1. Inform volunteer about data sharing can be explained in a sense that volunteer who is sharing his/her information is informed about the use of data and right he/she would have about data. The data collected for this thesis is only for research purpose [8]. Moreover volunteer should have right to decide what need to do about data. For example, if he/she want to delete some part of data etc. In this way, the privacy of volunteer can be protected in a better way.
2. The security of data means that the data should place in secure location so that no un-authorized person has access to data [8]. The security of data depends upon the technology and process through which data is stored. Moreover, it also covers that the data should be stored in its proper format so that while access data again there should be no corruption of data.
3. The anonymization of data is important part in the privacy of the volunteers. For example, the use of pseudonyms and reduction in location accuracy by truncation around important places such as home, office etc. The authors in [35] explain in detail about location anonymization using hybrid method.

4. It is also very important to inform the researcher about the privacy policies of data he/she using for research. In this way, the volunteer privacy can be protected. Moreover, researcher should have access to anonymized data. This will improve the privacy protection [8].

4.1.1 Ethical Issues

"It is not just how you use the technology that concerns us. We are also concerned about what kind of person you become when you use it" it was said by group of Amish leaders [36]. It means that the way technology is used to collect personnel data of people is of great importance for both; the collector of data and the person whose data is being collected.

According to Microsoft's Kate Crawford, this huge amount of data collection leads us to "Big Data" fundamentalism [36]. The Term "Big Data" means the collection of large number of datasets that cannot be processed with normal handle processing units (computers). This thesis is also processing a part of this "Big Data" that was collected from large number of people known as Mobile Data Challenge ("MDC"). MDC is large scale data collection from Smartphone based research [8]. It is clear that the data we collect is by nature neutral. The way we analyse the data and the way we act upon the data has important consequences on human [36].

Moreover, the privacy is basic human right which is made clear by the EU Justice Commission as well [36]. From the above statements, it seems that dealing with data provided by consumers in a sense in which he/she allowed is cleared and need to be followed strictly but still the data has been misused. For example, a state can use censuses for different good reasons including city planning, new job opportunity creation etc. but censuses can also be used by state to distinguish people from different race, culture and region that create problem for people if they do not want to highlight these things.

4.1.2 Potential threats

It means by keeping in mind ethical issues related to data handling/interpretation we can avoid potential threats to misuse of collected data. On March 4, 2014, Workshop about "Big Data" at MIT highlights important issues and benefits of "Big Data". White House advisor John Podesta, head of the presidential study on the future of privacy and big data, says that big data is big deal. He further says that big data helps to predict future behaviour [8]. Things that even one cannot himself/herself know are predicted. This can be considered as benefit in particular sense but on the other hand can be threat for person as well as for his/her personal life. After studying the mobility behaviour of particular person, we will be able to predict person's mobility and location in advance which will actually interference to his/her personal life. There are various benefits that can be achieved by proper analysis of "Big Data" in the field of medical, future resource planning (like road, cities etc.), driving safety etc. study shows that, young riskiest driver have shown 72% risk reduction if they know that they are being monitored [36].

4.2 Indoor data collection

The data gathering is a challenging task because the amount and accuracy of data depends on the type of model. Moreover, the sensor placement for data collection has significant effect on measurements. The type of technology used for data collection has also important impact on measurements. The following questions need to be addressed when selecting of technology for the data collection.

- Types of parameters to be collected
- Accuracy of measurement required
- Range of system required
- Rate at which measurement is required
- Complexity of measurement system
- Cost of measurement system
- People privacy consideration

4.3 Overview of indoor positioning methods

There is no indoor technology on large scale for indoor data collection. The following technologies are explained here briefly:

1) Wi-Fi based technology
2) Cellular based technology
3) Bluetooth based technology
4) Digital TV based technology
5) Assisted GNSS based technology

There are different methods which are used to calculate the position of an object based on data received from different technologies. These include [37];

- **Triangulation:** It deals with range or/and direction from/to known point (also called reference point).
- **Fingerprinting:** It deals with 2 stages, offline and online.
- **Dead Reckoning:** It starts from known location and calculate direction and displacement.
- **Hybrid:** It is combination of different methods.

4.3.1 Wi-Fi based technology

The Wi-Fi based technology operates at 2.4 GHz or 5GHz frequency band. The following are two main techniques which Wi-Fi used to estimate the location of target:

1) Received Signal Strength (RSS)
2) Time Difference of Arrival (TDOA)

1. RSS is a simple method in which the distance is calculated based on received signal level. Here we do not need to change the architecture of the device itself rather any device of capable this technology can be used directly to estimate the location. There are two different ways of RSS implementation, client based or network based. In client based, a Wi-Fi receiver receives various power levels from different access points and the measurement is performed based on database taken from clients. In the network based, a Wi-Fi mobile transmitter transmits to multiple access points. The access points perform the RSS measurements. The main disadvantage of this method is a large error in measurement due to the variations in signal level, caused by shadowing, multipath, body loses etc. Due to different environment conditions, signal level varies a lot. For example, the signal coming through wall and glass have different strength even though the distance is same in both cases.
2. TDOA is based on difference of arrival time between different messages that arrive to access points. The major flaw of this technique is that, the access point should be synchronized.

The following are the main advantages of Wi-Fi based technology:

- Already available standard architecture can be used.
- Operating capability even in Non-Line-of-Site (NLOS).
- Indoor range of few tens of meters.
- Cost is low.
- Installation process is simple.

The following are the main disadvantages of Wi-Fi based technology:

- Due to RSS variation, the choice of a propagation model is difficult.
- Accuracy varies a lot with different factors such as environment, distance etc.
- Due to 2.4 GHz and 5 GHz band, there are interference problem.

4.3.2 Cellular based technology

The cellular based location estimation technology is widely available. There are many procedures available in cellular based technology, such as cell ID, Round Trip Time (RTT), Angle of Arrival (AOA), Received Signal Strength (RSS) and Assisted GPS (AGPS) on mobile phones. The following is the procedure of cell ID to estimate the location.

- In cellular network, each mobile station (MS) is camp on particular cell. Each cell has unique identity known as cell ID. Based on cell ID on which MS is camp, location of the MS can be determined. Here the problem is, in urban area cell range is approximately 500 meters while in rural area it is several kilometres. This means that MS location can be determined with this accuracy in particular cell.
- To improve the accuracy, two methods can be used. In Idle mode, each MS is monitoring/measuring the level of serving as well as neighbouring cells, it means based on signal level strength the distance can be approximated. Moreover, in dedicated mode/connected mode system has timing advance/round-trip time information from which we can determine the approximate distance.
- To improve the accuracy further, interaction point of serving and neighbour cell's serving area can be determined.

The following are the advantages of this technology:

- No extra infrastructure is required, as cellular network is already deployed.
- It work both in indoor and as well as outdoor.
- The cellular networks are designed to tolerate power failures.

The following are few disadvantages:

- The cellular based systems lacks flexibility and also high configuration cost.
- This data is not public rather it is operator property which causes some legal issues.
- If we want to increase accuracy we need to add new feature in existing system.

4.3.3 Bluetooth based technology

Although Bluetooth is not originally made for positioning but it has function that can be used to estimate the location. There are two different ways to estimate the location:

- Zone approach: In this approach, different nodes are deployed. The position of node through which device (carrying Bluetooth) is connected is considered as position of device. The accuracy of location depends on size of zone area.
- Signal level approach: In this approach, the signal level is measured and location is estimated based on distance calculation due to different received signal level from different nodes. The accuracy depends on how better network is deployed.

The following are the advantages of this technology:

- Cheap technology.
- Low power transmission required (long battery life).
- Less interference (as low power is transmitted).

The following are the disadvantages:

- Due to multipath propagation, accuracy is not good.
- Range is small due to low power transmission.

4.3.4 Digital TV based technology

In Urban areas, the broadcast signals of digital TV can be used for localization. Indoor positioning with 10 m accuracy can be achieved. Pseudorange estimation is done without any modification in transmitted signal. (TOA) pseudorange is determined by synchronization of digital TV emitters and GPS time.

The following are advantages of digital TV based positioning [38].

- Signal power is larger as compare to GPS.
- High signal bandwidth, allowing multipath mitigation.
- Implementation is simple.

The following are the disadvantages:

- Only 2D positioning is possible.
- High complexity and cost.

4.3.5 Assisted GNSS based technology

The assisted GNSS helps to improve the indoor positioning when GPS signal is weak. When the signal is weak, GPS receiver cannot demodulate the navigation data. Without navigation data, there will be no GPS time and orbit parameters and as a result no positioning information. The major benefit of assisted GNSS is that it can work in weak signal by decreasing signal search space.

Table 4.1 shows the comparison of various positioning methods.

Table 4.1. Comparison of different positioning technologies

System category	***Range***	***Accuracy***	***Complexity***	***Cost***
Wi-Fi based	medium	medium/low	low	low
Cellular Based*	long	high	high	high
Bluetooth Based	short	medium	low	low
Digital TV Based*	low	high	high	high
Assisted GNSS**	low	low	high	high

*   indicates that TOA method is used

** indicates that indoor method is used

4.4 Thesis measurement data

The data used in this thesis is collected through “The Lausanne Data Collection Campaign (LDCC)” [39]. This campaign was conducted on huge level for data collection from smart-phone which reflects daily life actives. Although there is lot of different kind of data gathered but this thesis is related to GPS data containing coordinate of different users, representing movement pattern. Table 4.2 shows some type of data gathered during LDCC [8].

Table 4.2. LDCC data gathering types

Type of Data	*Amount*
Number of Calls (in/out/missed)	240,227
Number of SMS (in/out/failed/pending)	175,832
Number of Application events	8,096,870
Location points observation	26,152,673
Unique cell towers observation	99,166
Bluetooth observations points	38,259,550
Unique Bluetooth devices	498,593
WLAN observations points	31,013,270
Unique WLAN access points observation	560,441

The authors in [8] explain in detail the procedure used for LDCC design and other information related to data types.

5. MEASUREMENT ANALYSIS

This chapter describes about how the data is collected from the third party and what type of information is stored in it. Moreover, it also describes that how different parameters are extracted from the given set of data to utilize in the user mobility models. At the end, it presents some examples of our outdoor measurement data analysis.

5.1 How we got the data?

The data used in our measurement analysis was achieved under this Mobile Data Challenge ("MDC") sharing agreement. According to this agreement, the eligible institutions are universities and non-for-profit, civilian, academic research institutions worldwide. All research done with the MDC dataset should strictly be for non-commercial and ethical purposes [40].

The following instructions must be taken into account when using this data for research purposes [40].

- In this agreement, the Licensor permits Institute a license to use the MDC data ("Database") [40] in subject to the confirmation of the acceptance given terms and conditions.
- Each permitted staff from the Institute may only use the Database after the corresponding agreement has been signed and returned to the Licensor.
- The Institutions are not allowed to distribute data in any way, permanently or temporarily, transfer of broadcast all or part of the database to third parties.
- The use of this data for commercial purpose is not allowed.
- The data is allowed to be used under this agreement for achieving high goals in the research field, while maintaining in a way that any Institution shall not process the Database in a way in order to reveal personal sensitive information of each individual participating in the Database.
- All the publications should reference the original publications.

5.2 Parameters description

The authors in [40] mentioned in details about the collection of data. The following input parameters were stored in the GPS dataset:

- Time (in days)
- Latitude (degrees, converted to meters)
- Longitude (degrees, converted to meters)
- Altitude (in meters)
- Speed (in km/h)
- Horizontal-accuracy
- Horizontal-DOP
- Vertical-accuracy
- Vertical-DOP
- Speed-accuracy
- Time since GPS boot

In this thesis work, the first five above listed parameters of various users are used in order to summarize the behaviour or mobility pattern of different users jointly.

5.3 Anonymization procedure

The anonymization is an important procedure in order to hide the potentials location of the user. Actually, the main objective of collecting data from the users was for research purpose [8] that is way, the privacy of each individual who is participating in this Database [40] should be protected.

Moreover, in order to make the user privacy in a better way, this should be carefully considered that personal data of the user should be placed in a protected location, so that un-authorized person should not access the sensitive information of each individual [40].

In the GPS measurement data analysis presented in this thesis, the last two digits of latitude and longitude input parameters were cut-off because the anonymization of data is important part in privacy of volunteer. For example, the use of pseudonyms and reduction in location accuracy by truncation around important places, such as home and work place, etc. In [35], the authors explain in details about the location anonymization using hybrid method.

5.4 Measurement analysis of users

The following are the examples of plots x-y of different users exhibit the distance versus time, speed versus time variations etc.

Figure 5.1, Figure 5.3 and Figure 5.5 show the time versus distance plots for three users, named here as: user 1, user 2 and user 3 respectively. Figure 5.2, Figure 5.4 and Figure 5.6 show the speed plots of each of the three users considered above. There are some short and long sudden peaks in the plots which show that there are some errors in the GPS measurement data or probably due to the missing data. Also, there is no data available between various days which mean that the user is not tracked between these days due to unavailability of GPS.

5.4.1 Example user 1

Figure 5.1 illustrates that the user was tracked for 14 days in total, and each day the user travelled a particular distance shown in the plot. It also describe that the sampling interval is not constant, in some days it is shorter time interval while it is longer in other days.

Figure 5.2 shows that the speed is approximately zero when the user is stationary, while, the average speed is typically 5km/h which is a normal speed of human walk. The user 1 has travelled with a maximum speed of about 33 km/h.

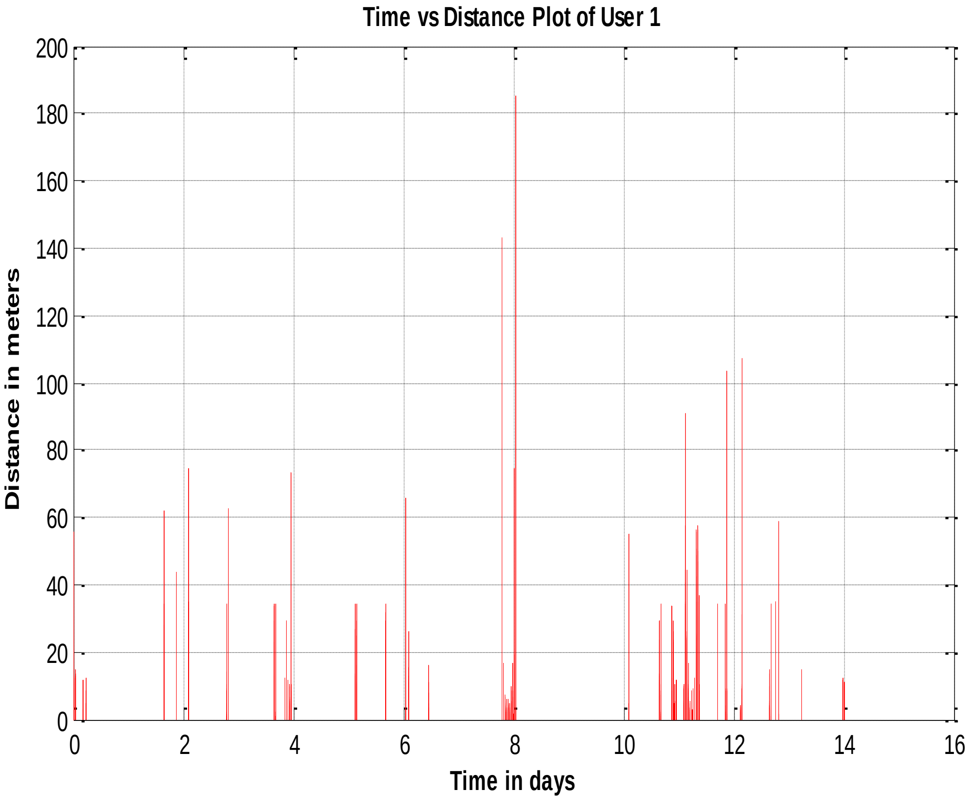

Figure 5.1. Distance (meters) versus time (days) variations of user 1

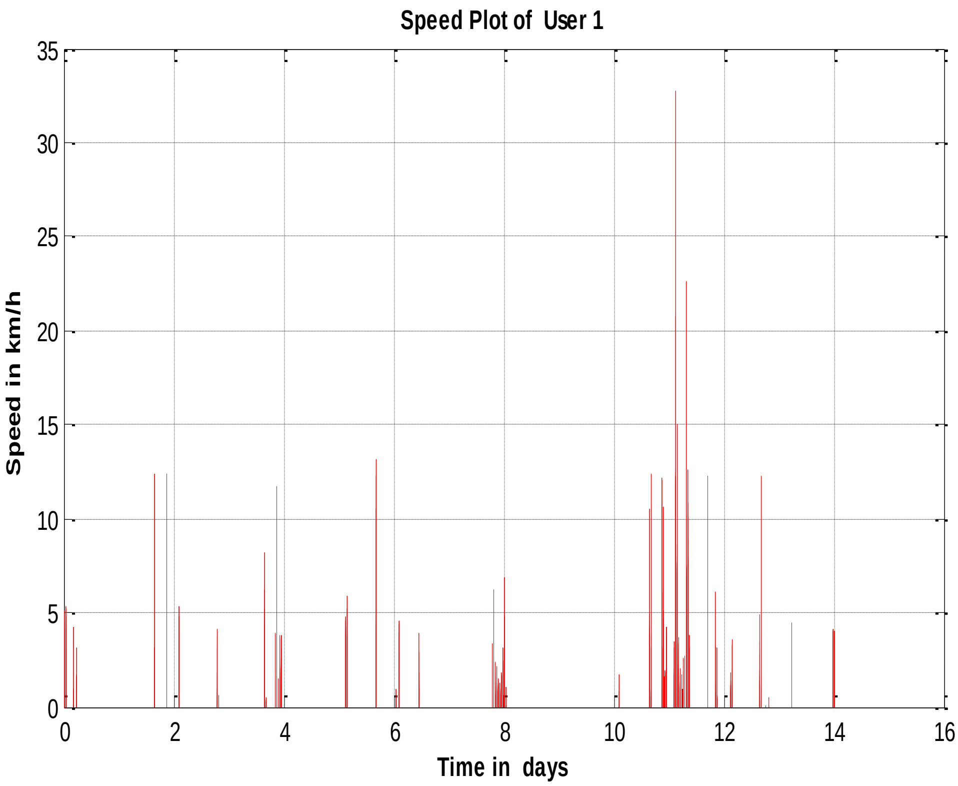

Figure 5.2. Speed (km/h) versus time (days) variations of user 1

5.4.2 Example user 2

Figure 5.3 describes that the user 2 was tracked for almost 141 days. Also, it can be seen that the sampling interval is constant for most of the days but data is missing between days 110th to 140th (i.e., for a long time duration).

Figure 5.4 shows the speed fluctuations per day in km/h of the example user 2. We can see that, the user 2 speed is generally constant because of following a regular movement pattern.

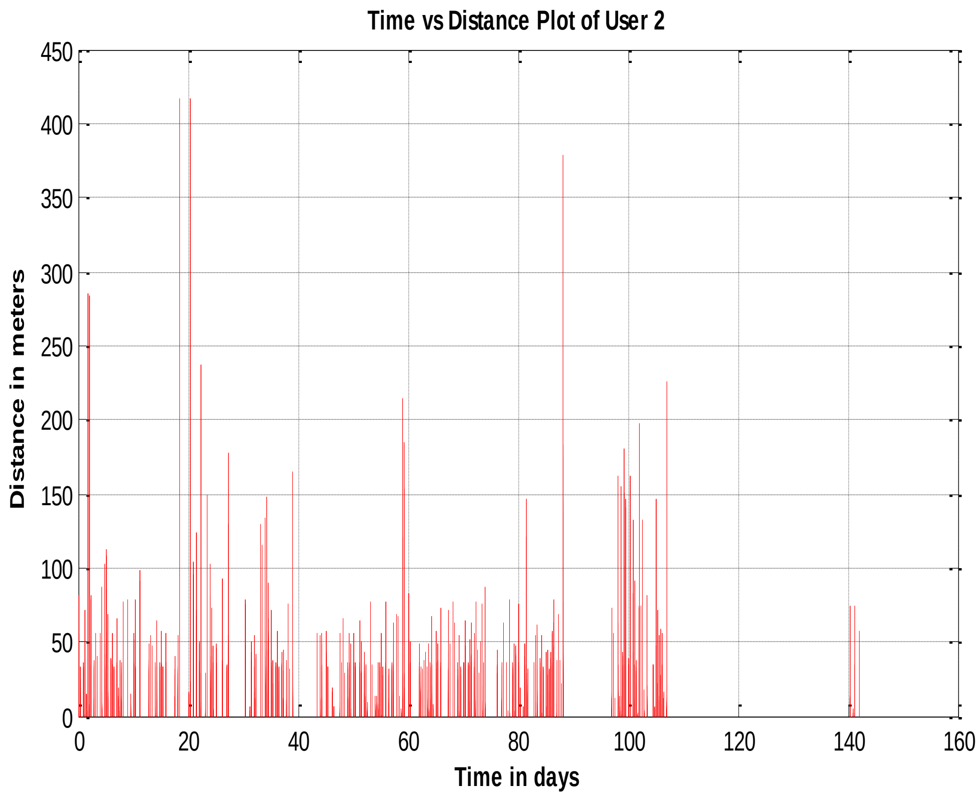

Figure 5.3. Distance (meters) versus time (days) variations of user 2

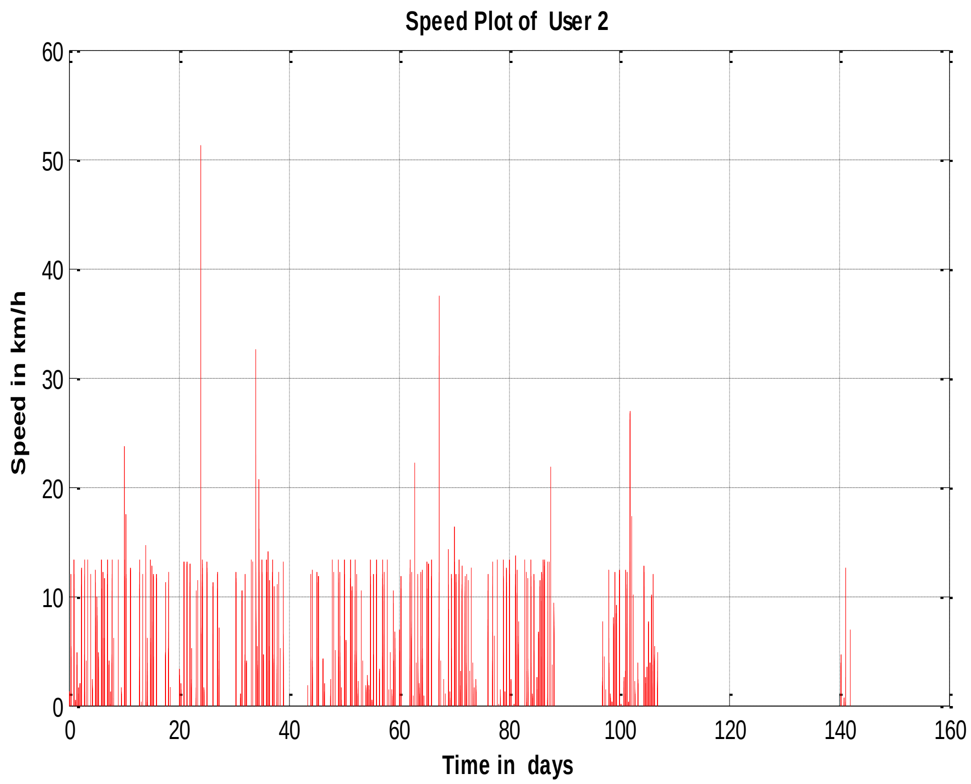

Figure 5.4. Speed (km/h) versus time (days) variations of user 2

5.4.3 Example user 3

Figure 5.5 illustrates that the user was tracked for 32 days and this user exhibits a constant pattern of travelled distance. This regular movement pattern shows that the user is normally following a particular route from one location to another. It can be distinguish day and night time of this user.

Figure 5.6 shows the speed fluctuations in km/h for the user 3, and it illustrates that the user 3 speed is around 13 km/h and it has travelled with a maximum speed of about 18 km/h.

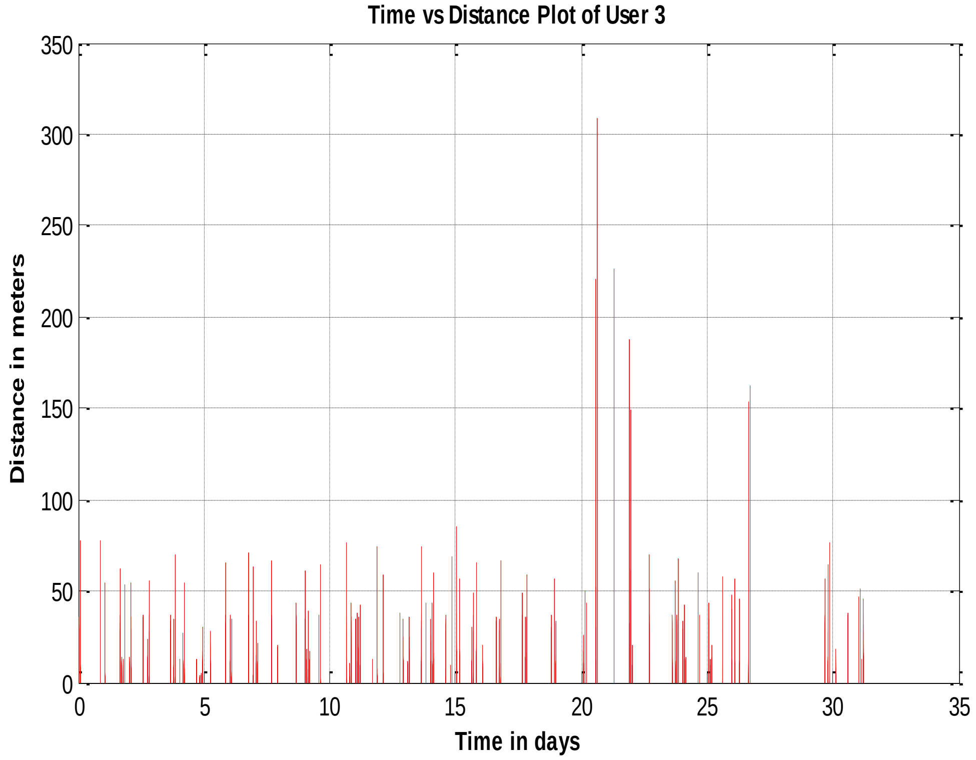

Figure 5.5. Distance (meters) versus time (days) variations of user 3

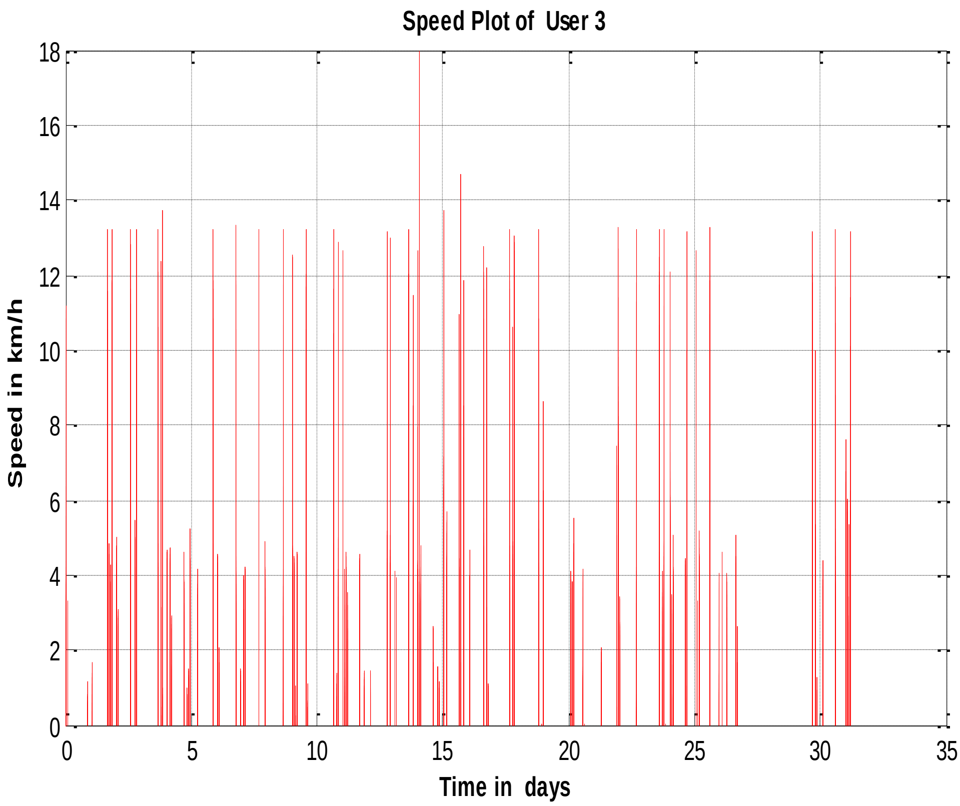

Figure 5.6. Speed (km/h) versus time (days) variations of user 3

6. MODEL FITTING

In the model fitting chapter, the main analysis results of the available GPS user data are presented and also these results are compared with a random walk model.

6.1 Statistics of GPS measurement data

Table 6.1 indicates the mean and median statists over all users of GPS measurement data. Table 6.2 presents the statistics of GPS users per day.

Table 6.1. Statistics (Mean, Median) over all users (185 users) of GPS measurement data

Parameters	Mean	Median
Speed per user [km/h]	0.4065	0.2358
Δx step [m]	91.7316	0.5629
Δy step [m]	92.7786	0.5312
Δz step [m]	3.4440	0.4886
Δt step [s]	277.7339	10
Angle [rad]	0.1632	0.3825

Table 6.2. Statistics (Minimum, Average, Maximum) of GPS users (185 users) per day

Average speed per day [km/h]	1.5597
Average distance done in one day [km]	1.1234
Maximum of maximum distance done in one day [Km]	4.4819
Average time per day when measurements were done [hours]	0.2401
Max time per day when measurements were done [hours]	0.3161
Average total time of tracking one user [days]	319.7409
Maximum total time of tracking one user [days]	566.8917
Minimum total time of tracking one user [days]	0.7585

As it can be seen in above that the mean values are likely to be affected by errors, and this explains the strange large mean values in the steps, thus median values are more reliable.

6.1.1 Plots of statistics in GPS data

Figure 6.1 shows the mean and median speed per user in [km/h]. The mean value of all GPS user measurement data is 0.4065, while, the mean speed typically lies between 0.8 to 2.0 levels. Similarly, the median of all users is 0.2358 and median speed varies between 0.5 to 1.5 levels. Figure 6.2 illustrates the x step in [meters] over all GPS users. The mean and median x step is 91.7316 and 0.5629 respectively. The mean and median of x step shows abrupt changes for the early 20 users but these are constant for rest of the users between 40 to 110 levels and 0 to 1 levels respectively.

Figure 6.3 presents the y step in [meters] for all users. The mean and median values for the y step are 92.7786 and 0.5312 which are almost the similar to x step and also the variations levels are same as it can be seen in the both plots. Figure 6.4 exhibits the z step in [meters] over all users. The mean and median values are 3.4440 and 0.4886 respectively. The mean of z step varies between levels 2.5 to 4, while, the median lies between 0 to 4.5 levels. Figure 6.5 describes the t step in [seconds] which is computed as a time difference between successive measurements, the mean and median of t are 277.7339 and 10 respectively. The mean of t step varies between levels 0 to 500 levels and median is a constant value at level 10.

Figure 6.6 illustrates angle in [radian] over all GPS users. The mean and median values of angle are 0.1632 and 0.3825 respectively. The mean of angle peaks varies between levels 0.05 to 0.25, while, for the median these lies between 0.1 to 0.6 levels. Figure 6.7 shows the duration of measurements per user in days. The average total time of tracking one user is around 319.7409 days, the maximum total tracking time is almost 566.8917 days and the minimum total time of tracking one user is about 0.7585 days.

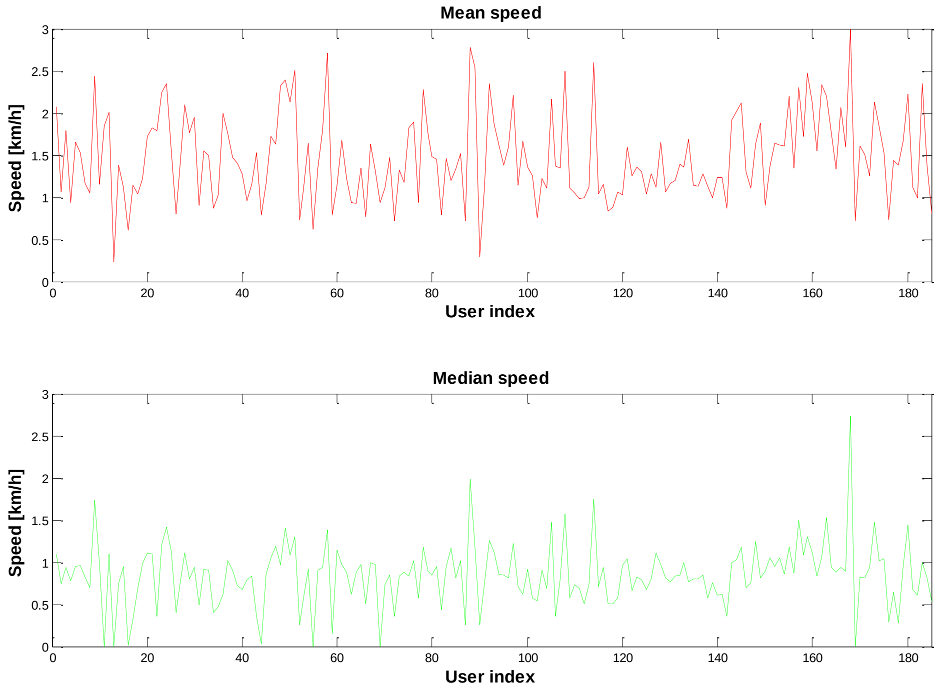

Figure 6.1. Mean and median speed per user [km/h]

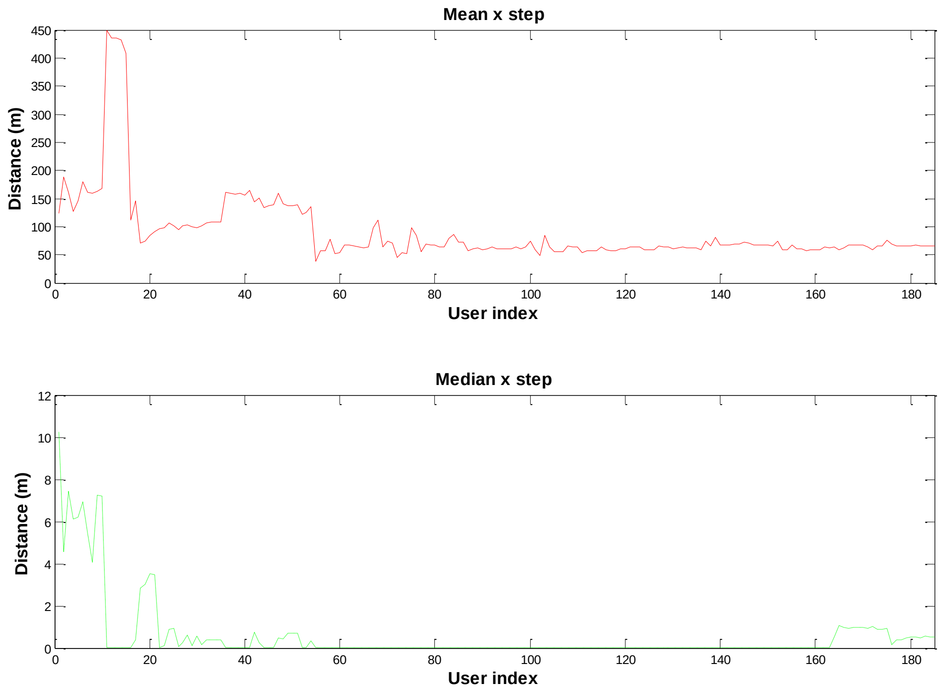

Figure 6.2. Mean and median x step [m] per user

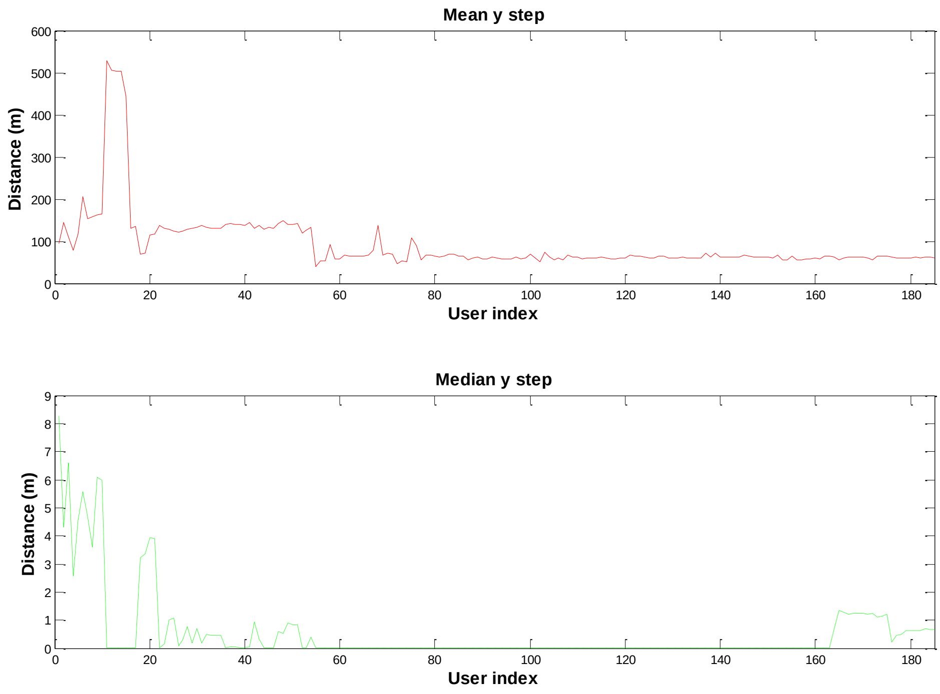

Figure 6.3. Mean and median y step [m] per user

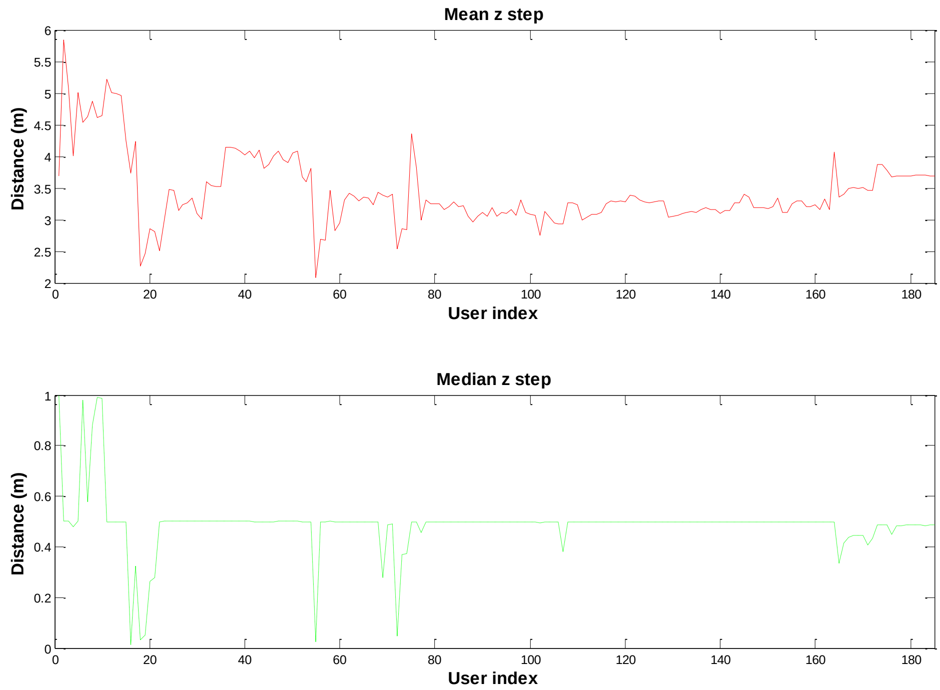

Figure 6.4. Mean and median z step [m] per user

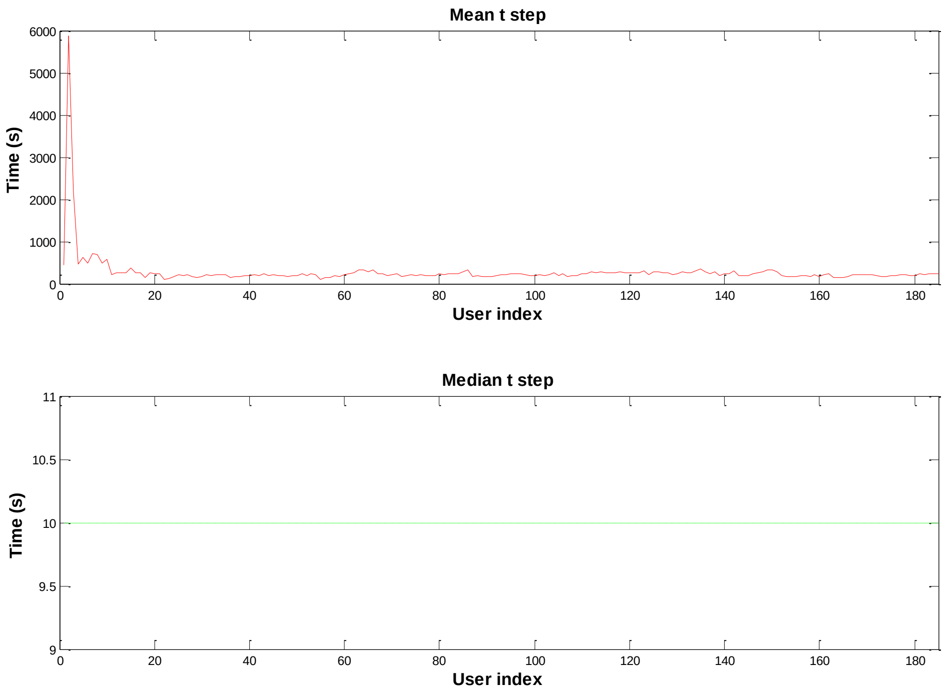

Figure 6.5. Mean and median t step [s] per user

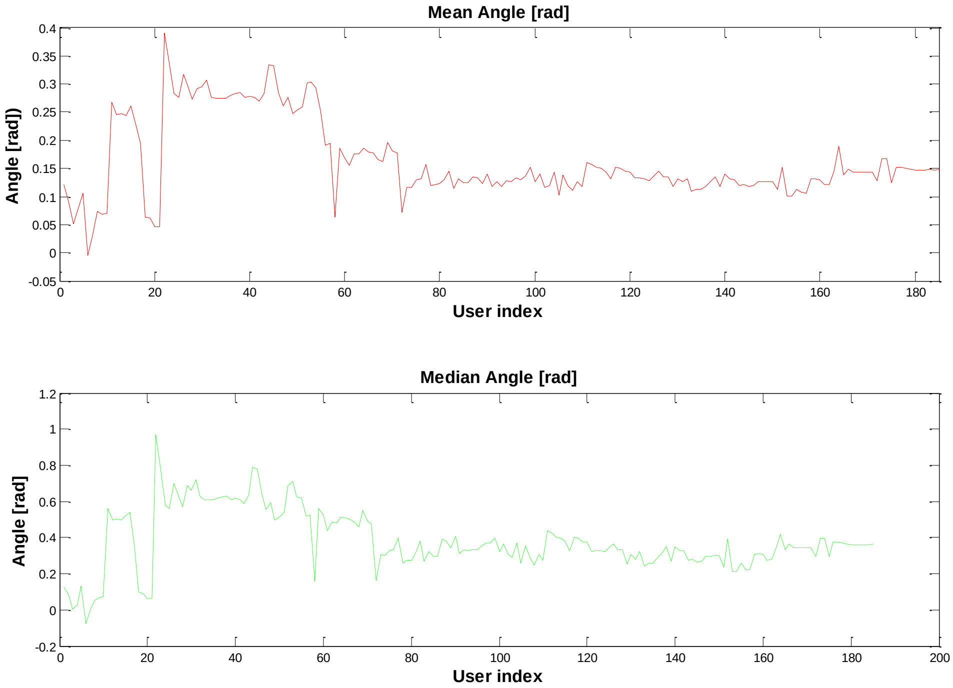

Figure 6.6. Mean and median angle [rad] per user

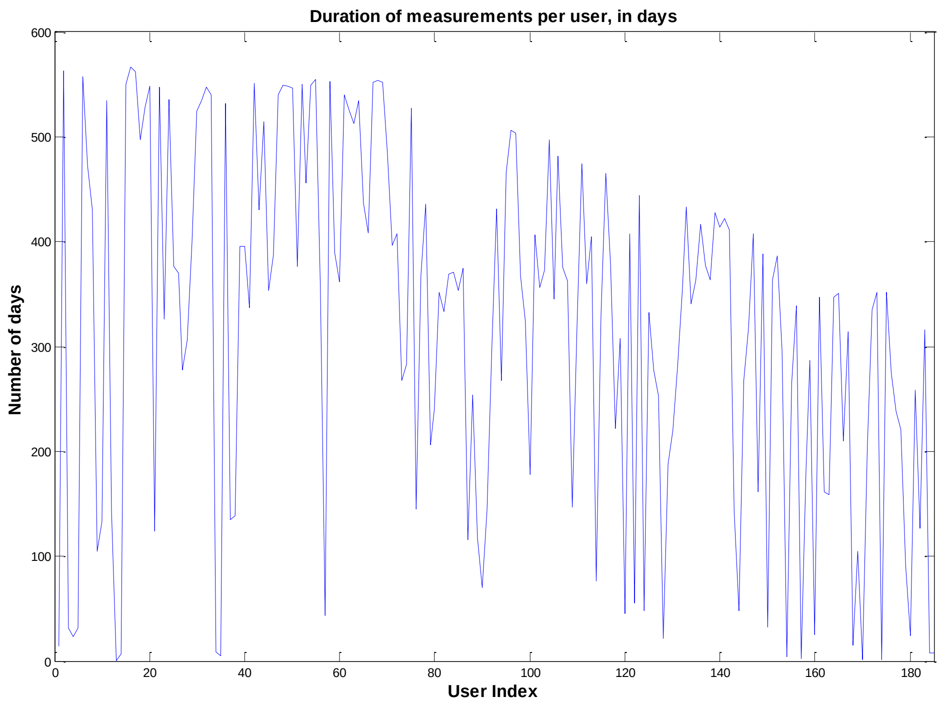

Figure 6.7. Duration of measurements per user in days

6.2 Mobility model parameters

In the mobility model parameters, we try to see how a basic mobility model, namely the random walk model, fits to the GPS user data. The approach was as follows:

- The histogram of the measurement–based parameter was computed.
- Several theoretical distributions with best parameter fit were tested against the measured histogram.
- Kullback Leibler (KL) divergence criterion was used to compare the measured and theoretical distributions.

An example plot is shown in the Figure 6.8 to illustrate the concept of theoretical pdf and the measured pdf.

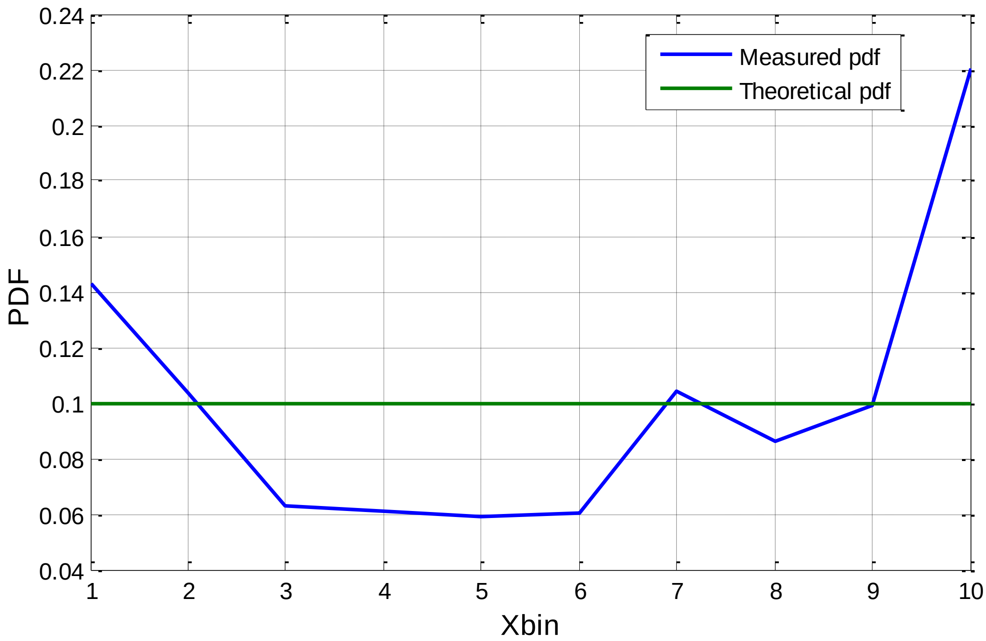

Figure 6.8. Theoretical and measured pdf

The KL divergence plots are shown in Figures 6.9-6.10. Basically, a lower KL value shows a better fit than a large KL value. A best fit would occur for 0 KL. Figures 6.9-6.10 show the random walk model parameters, such as the angle change and the step change and how they fit to the KL divergence with various tested distributions. KL divergence compares the two pdfs.

Figure 6.9 shows the KL divergence for the angle change tested against two different distributions, namely uniform distribution and normal or Gaussian distribution. It can be observed that the uniform distribution is a better fit to the angle data than the normal distribution. Indeed, according to the random walk model, angles are uniformly distributed.

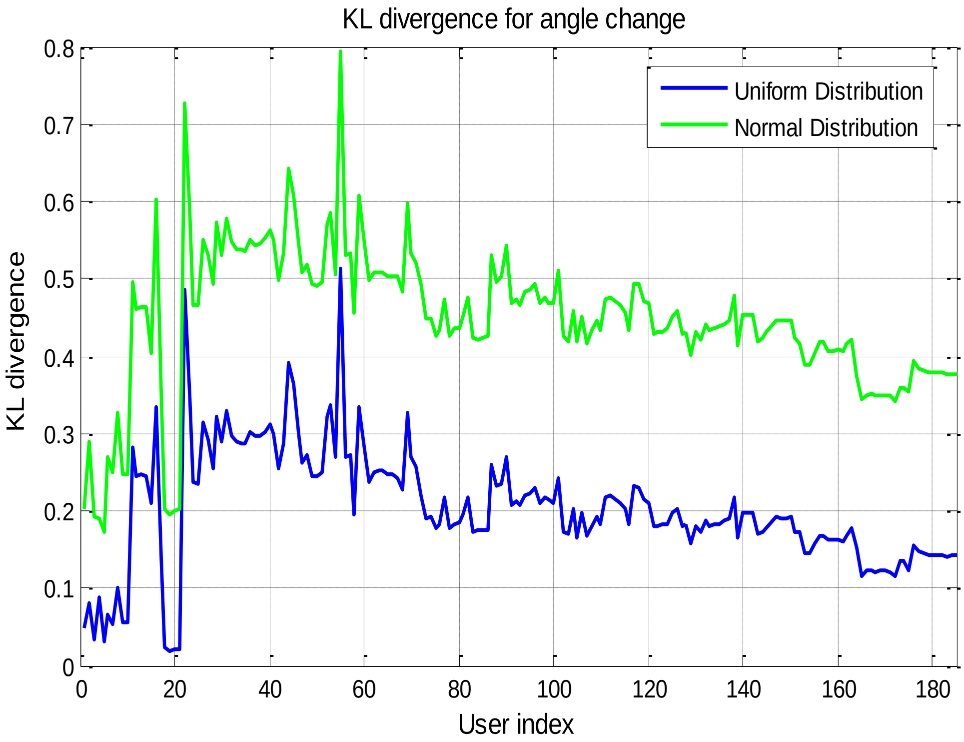

Figure 6.9. KL divergence for angle change

Figure 6.10 shows the KL divergence for the step change tested with four different distributions, namely exponential distribution, Poisson distribution, uniform distribution and normal distribution. It can be observed that KL is very low for exponential distribution than rest of the distributions, thus the exponential fit is the best fit to the step data among the four tested distributions. According to the theory, the step parameter in the random walk model obeys a truncated power law distribution, which was not tested here due to lack of time. Exponential distribution is however the closest to a truncated power law distribution.

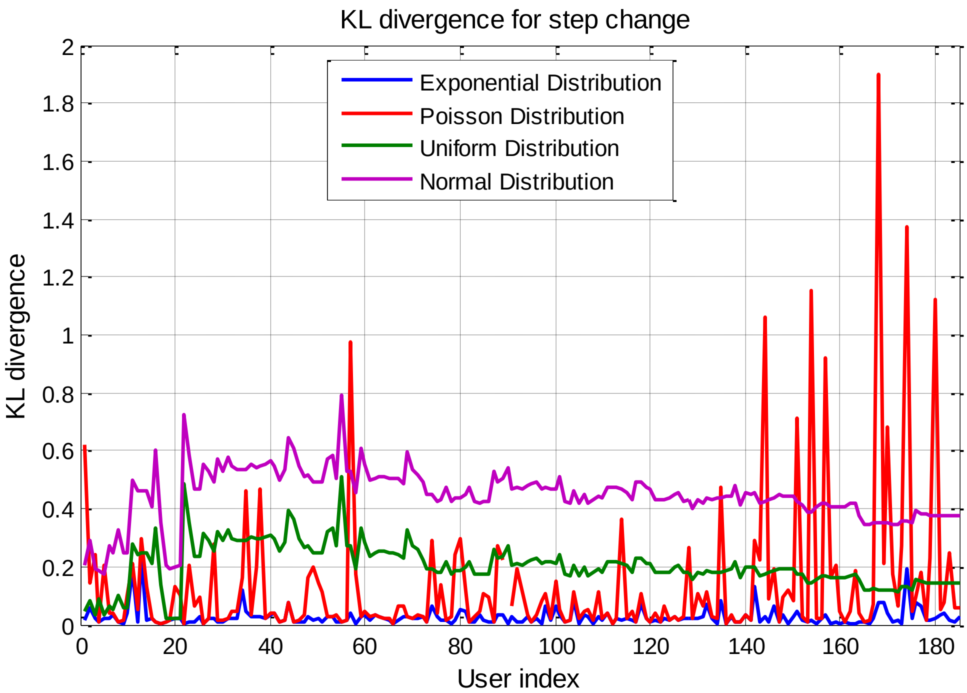

Figure 6.10. KL divergence for step change

7. APPLICATION AREAS

This chapter mainly discuss the application areas where the user mobility models are important and helpful for human beings e.g. in VANET (Intelligent transportation), MANET (performance analysis of MANET routing protocol) and DTN network, e-health care, traffic dimensioning from operator side, advertisement and in so many other routine life applications.

7.1 Intelligent transportation system (ITS)

Due to increasing population around the world also causes great increase in number of vehicular to carry out routine life activities. That is the reason why, this increasing number of traffic produces great challenges in traffic planning. In order to meet these challenges, vehicular ad hoc networks (VANETS) communication is the leading technology for the improvisation of road collisions and ease while through intelligent transportation system (ITS). The VANET communication purposed the vehicular mobility models both at macroscopic and microscopic levels which can be implemented to provide precise and more accurate vehicular mobility description [41].

The smart way of implementing vehicular mobility models can introduce the following benefits:

- Increasing traffic safety can save lives.
- Increasing traffic efficiency is helpful in order to avoid traffic jams.
- Increasing environment friendliness can reduce the CO_2 emission.
- Warning about accidents ahead can increase the road safety.
- Increasing the efficiency due to changing different routes can save the fuel consumption.

Similarly, the other examples of intelligent transportations system application include; intersection violation warning, electronic brake warning, vehicular stability warning, lane changing warning, pedestrian in road warning and on-coming traffic warning.

7.2 Performance analysis of MANET routing protocol

The mobility models are also useful in mobile ad hoc network (MANET) applications. Basically, MANET consists of collection of mobile nodes which can move freely without any predefined infrastructure where each node is logically acting as a router for communication with other mobile nodes. MANET is not yet implemented on large scale applications, but it is widely used in military services applications [42].

Therefore, the right selection of existing mobility models can increase the performance of MANET routing protocol. Similarly, these models can also be useful in performance analysis of MANET proactive and reactive routing protocols over different mobility models [42].

7.3 Data collection in wireless sensor networks

Wireless sensor networks (WSN) normally consist of large number of sensor nodes which are capable of capture, process and transmit useful information from that region to base station. To accomplish this whole process, WSN needs multi-hop routing to transmit this sensed information to base station, so in relaying data mostly the sensor's energy is consumed which causes non-uniform depletion in the network energy. Therefore, the node near base station expires quickly and the communication with the base station terminates [43].

Therefore, mobility has been suggested as a solution to overcome the network energy deficiencies concerning about multi-hop routing. While adopting various approaches, such as controlled mobility, random mobility and predictable mobility it is possible for a mobile element to achieve its ultimate data collecting goals. Controlled mobility in WSN brings following benefits [43].

- Optimization of the network performance
- Prolongation of the network lifetime

7.4 E-health care services

The e-health care services are getting popular these days because of their low cost and convenience in use. These health care services are performed by electronic processes and communication. For example, old or disabled people need great care, especially when they are performing outdoor activities. An abrupt fall in elderly or disabled people may be common and it is difficult to prevent falls in old patients. Moreover, it is also difficult to handle situation for those patients with serious diseases. But it is possible to assist them by reducing the time of treatment or providing them on time e-health services [44].

By developing efficient decision making algorithms, fall detectors and mobility models, it is possible to monitor and supervise elderly and disabled people more efficiently and to assist them within short time and help them to improve their health activities. The efficient mobility models in e-health care system brings following benefits:

- Enable better, safer and easier health care monitoring for elderly and disabled people than currently existing approaches
- Improve patient safety
- By providing health care closer to home, one can reduce the travel time

7.5 Advertisements

Advertisements (Ads) are one of the most important sources of revenue for big companies around the world. Therefore, with the development of suitable predictable mobility model for the delivery of advertisement, it is possible to achieve the high goals of generating big revenue.

Moreover, mobility models can be used in so many other applications, such as;

- Localization algorithms for elderly care and monitoring applications.
- In cellular communications networks to avoid traffic congestion.
- Mobility model can be used to design such systems which can predict prior user location.
- In future, this model can be used for public transportation applications.

8. CONCLUSION AND OPEN ISSUES

This chapter summarizes the conclusion of this master thesis research work and it also addresses future directions and open challenges.

8.1 Conclusion

In this thesis, the classifications of human mobility parameters were discussed, such as spatial, temporal and social dimensions. Further, various basic existing entity mobility models were addressed in order to select an appropriate and simplified mobility model which could be analysed with the available real field GPS measurement data. In chapter 4, the overview of indoor positioning technologies and data gathering issues, such as the user privacy issues, was presented. In the measurement analysis chapter 5, it was described that how the measurement data was obtained and also the parameters that were utilized to our proposed models. Some examples of plots x-y of various users can also be seen from Figures 5.1-5.6.

In model fitting chapter 6, the analysis of available GPS measurement data of all users was performed in MATLAB and statistics of different mobility parameters were presented that can be seen from Figures 6.1-6.7. In addition, Table 6.1 described the mean and the median statics of mobility parameters which were done over all user data and Table 6.2 represented the statistics per day. After careful analysis of obtained results, the parameters were implemented to the proposed basic mobility models, namely 2D random walk model. At the end, many different useful practical applications of human mobility models were discussed briefly. These applications can be implemented in many areas, such as public transportation, performance analysis of MANET routing protocol, e-health services, and advertisements.

In conclusion, the random walk model parameters, namely the angle and step were tested and observed how they better fit to KL divergence with various distributions, namely uniform distribution, normal distribution, exponential distribution and Poisson distribution. After careful analysis, it was observed that the random walk model is not good fit to the available user measurement data as it can be seen in form Figures 6.8-6.9. There is still need to do more sophisticated research in order to investigate other human mobility models, so that these models could be useful in many practical applications for the benefits of mankind.

8.2 Future directions and open challenges

This is an initial struggle toward this wide field of user mobility models and algorithms and there is still room available for further enhancement and improvements for the continuation of this work. There are many potential ideas that are not implemented due to the time limitations, such as the extracted GPS parameters can be implemented with the Levy walk model and results of it can be compared with the random walk model in order to determine which one is most feasible to the measurement data.

The suggested basic mobility models and algorithms can also be investigated further with other tuning parameters of GPS measurement data such as horizontal accuracy, horizontal DOP, vertical accuracy, vertical DOP and speed accuracy etc. Moreover, the currently extracted GPS parameters in this thesis work can also be implemented with 3D random walk model and other human mobility models.

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