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Energy Aware Node Mobility Prediction in Mobile Adhoc Networks

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Abstract—The analysis of human location histories is currently getting an increasing attention, due to the widespread usage of geopositioning technologies such as the GPS, and as well as online location-based services that allow users to share this information. Tasks such as the prediction of person's movement can be addressed through the usage of this data, in order for offering support for more privileged applications, such as adaptive mobile services through proactive context-based functions. Here we aim to develop a simple and effective scheme to predict when the user will leave from the current location and where he will move to future position. This paper presents a hybrid method for predicting human mobility on the basis of Mobility Markov Chain Models (MMCs). The proposed approach clusters location histories according to their characteristics, and latter trains the MMC model based on mobility history to obtain transition matrix. The usage of MMC allows us to take information of location characteristics as parameters, and also to account with the effects of each individual's previous actions. The proposed system is a mobility prediction with adaptive duty cycling approach in reducing energy consumption, with a mobility model called Mobility Markov Chain (MMC) for predicting the future location. We report a series of experiments with a real-world location history dataset and from the Life Map dataset, showing that the prediction accuracy is in the range of 65 to 85 percent.

Keywords—Mobility, Next Place Prediction, Mobility Markov Chain Models, Energy Efficient.

I. INTRODUCTION

The widespread usage of localization systems, such as the Global Positioning System (GPS), is making it possible to collect interesting data in many different domains. Modern geopositioning technologies have become ubiquitous, and there are nowadays many possibilities for effectively tracking the position of individuals over time. Simultaneously, location-based social networks such as FourSquare1, or GPS track sharing services such as GoBreadCrumbs2, are nowadays being increasingly used as a means to store and share human location histories. Mobile Ad-hoc Networks (MANETs) is a set of wireless mobile nodes configured to communicate amongst each other without the aid of an existing infrastructure. MANETS are the Multi-Hop wireless network since one node may not be indirect communication range of other nodes. In such cases the data from the original sender has to travel a number of hops in order to accomplish the objective. The transitional nodes perform as routers and forward the data packets till the destination is reached. Like other networks the performance of ad hoc networks is affected by its topology. Many mobile applications for smart phones require position in-formation, and the usage of these applications is rapidly increasing [1]. For instance, many mobile services such as mobile search, advertisement, social networking, and mobile gaming heavily use users' position information to provide location informed responses to search queries or to continuously log user locations. Fig. 1 represents an MANET networks containing four nodes which are A, B, C and D which shows the ongoing nodes in a network. Keeping in mind about human mobility provides useful information for urban planning, traffic engineering, predicting the spread of human and resource management in mobile communications [2]. It is essential to recall that mobility models should be able to ape the distribution and movement pattern of nodes as in real-life situations [2] [3]. The collection of the locations visited by individuals through mobile devices equipped with GPS or WiFi positioning has attracted a lot of the attention, both from the industry and the research community. Addressing the issue of predicting the next location of an individual based on the observations of his mobility behavior over some period of time and the recent locations that he has visited [2]. The main constraint of mobile nodes is their limited energy resources since their batteries are limited. One main feature is to lessen the energy utilization of the nodes in order to boost the duration of the system [3].

It has quite a lot of potential applications such as the estimation of geo-privacy mechanisms, the growth of location-based services which are anticipating the next movement of a user with the design of location-aware practical resource relocation system. In fact, in cellular networks, mobility prediction has been revealed to be extremely significant at both the network and application point. As mobile devices have become capable of locating them-selves almost all the time, a variety of mobile applications have emerged that seek to continuously track a user's location context. Supporting continuous sensing applications on mobile phones is challenging because of the resource demands of long-term sensing, inference and communication algorithms. A key challenge of continuous sensing on mobile phones is to process raw sensor (e.g. accelerometer, microphone, GPS, gyroscope, digital compass, and camera) and compute higher level inferences and representations of human activities and context – possibly in real-time and communicates these higher level inferences to the cloud [7]. Many emerging location aware applications require position information. However, these applications rarely use cell tower-based localization because of its incorrectness, preferring instead to use the extra energy hungry GPS [8]. An obvious choice for tracking a user's location context today is to periodically collect coordinates from available positioning systems (e.g., GPS) and directly provide them to applications. Point of interest is the physically defined by drawing a circle or a polygon based on the user visit, and paths are parsed from day-long traces by post-processing algorithms, if not done manually. However, we argue that such schemes fail in discovering many interesting indoor places, struggle to scale, and consume unnecessary energy. Most of the places we go and stay are indoors, and even a single building (or adjacent ones) can contain multiple places especially in dense urban environments [5].

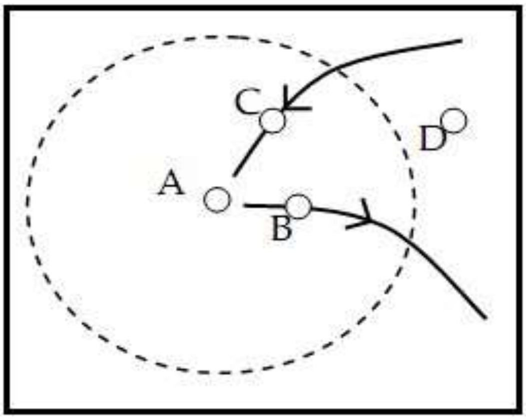

Fig. 1. Basic scenario in MANET's network

TABLE I. SUMMARY OF SYSTEMS

SUMMARY OF RELATED SYSTEM				
SYSTEMS	**POI**	**SENSOR USED FOR TRACKING**	**MOBILITY PREDICTION TECHNIQUES**	**EVALUATION PLATFORM**
Jigsaw[7]	Raw co-ordinates	Accel[a] , GPS	-	Iphone
CAPS[8]	Raw co-ordinates	GPS	-	Google Nexus
SenLoc[5]	Meaningful place	Accel[a], GPS	-	HTC G1
Smart DC[1]	Meaningful place	GSM, GPS, WiFi	MDP	HTC Desire
Iloc[9]	Meaningful place	GSM, WiFi	Viterbi Algorithm	Simulation on PC
LocP	Meaningful place	GPS	MDP, n-MMC	Sony Xperia U

Accelerometer used in Android Mobiles

The basic idea of this study is to maintain the history of user mobility patterns on mobile devices, and then to use that history in order to predict future locations. The proposed system is divided into two phases: the first phase is a continuous location tracking system with adaptive duty cycling for monitoring purpose; the second phase uses the history of user mobility patterns in order to predict the future next location of the mobile node.

Our main contributions are as follows:

(1) continuous location monitoring: places and paths in terms of latitudes and longitudes, (2) present a model that provides location tracking using less energy utilization, and (3) estimating the accuracy in prediction and energy cost utilization when used every day.

The key technical challenges in our work are:

(1) Simultaneous location tracking and prediction based on a user's mobility, (2) prediction of future location based on previous history, and (3) minimizing energy consumption.

We implement LocP on the Android framework as an application, and evaluated the scheme using traces of users for over six months in real environments. While the performance depended on a given energy budget, our extensive evaluation showed that LocP performs mobility tracing and prediction, and outperformed previous systems in terms of accuracy in prediction the future location and energy consumption. The following paper is planned as follow first; we review relevant related work study, the system model, implementation details, the data set which we are going to use and finally result analysis.

II. RELATED WORK

In this section, we describe a summarized table on the current systems, with respect to our system model. Table 1 summarizes the key features of related systems. All the systems are the continuous monitoring system use to monitor the mobility of the mobile node. We also discuss the proposed model which will be deployed on mobiles, based on the modeling of human mobility.

Jigsaw a continuous sensing engine for mobile phone applications which require continuous monitoring of human activities and context. Continuous sensing applications require careful resource management in order to facilitate long periods of data collection and processing. It uses sensor -specific pipelines that have been designed to cope with the individual challenges presented by each sensor. The techniques was developed are not tied to any specific application but are based on studying the specific problems that arise in mobile phone sensors and phone usage patterns. This system is a daily sensing system with low power architecture of sensor pipelines which is on the rise of interest and achievement of sensing applications on mobile phones [7]. The Jigsaw architecture comprises three classification pipelines that sit between the application layer and hardware sensors; these are accelerometer, microphone and GPS pipelines which are responsible for sampling, processing and classification of data from the sensors. Novel design ideas, flexibility and adaptability make it possible to deploy on various mobile phones for continuous location monitoring [1] [7] [13]. The Jigsaw accelerometer pipeline counters extraneous activities by recognizing: i) periods of user interaction with the phone, (e.g., a user texting); and ii) transition states such as standing up or picking up the phone. Jigsaw does not require the phone to maintain any particular body position and inference accuracy remains consistently high even when the body position changes.

Cell tower-based positioning systems use triangulation to estimate user positions. The Cell-ID Aided Positioning System (CAPS) achieves position accuracy comparable to that of GPS while achieving extremely low power usage. At its core, CAPS is based on the observation that, for mobile users with consistent routes, the cell-ID transition point that each user experiences can often uniquely represent the current user position [8]. Specifically CAPS estimates current user position using the cell-ID information freely available on smart phones, along with the history of past GPS coordinates. It stores cell-ID sequences and GPS readings taken by the mobile device during daily use in a sequence database, and then finds a matched sequence in his history using a modified Smith Waterman algorithm. With adequate history, CAPS can extract accurate position information from this sequence database without, in many cases, activating GPS [4], [8]. CAPS consists of three core components — sequence learning, sequence matching and selection, and position estimation — that are entangled. The sequence learning module populates a local sequence database with cell-ID sequences when it detects that the database has insufficient information about the cell-ID that the user currently is in. The sequence matching and selection component match the user's current sequence of recently visited cell-IDs with sequences learned in the database to find the best match sequence. The position estimation component uses the last cell-ID within the matched sequence to interpolate the user's position.

SensLoc runs in the background of the mobile device, places are gradually learned as a user visits them and spends a substantial amount of time. A new position is learned with saving its place signature whenever a visit to an unknown place is detected, and sometime later in the day asking the user to confirm a name for a place. It is a system based on location service to give appropriate information, abstracting location as place visits and path travels from sensor signals. It has a strong place detection algorithm, a responsive movement detector, and an on stipulate path tracker [5]. It has a new place visit inference process, take a fusion approach to collect energy, and track paths only when travelling among places. It uses place learning algorithms which attempt to find meaningful places from raw sensor data [3] [5]. We can broadly organize into two types: geometry based and fingerprint based approaches. It solves some of the major practicality issues with continuous location tracking. Iloc is system use for predicting person's geo-spatial traversal patterns using a history of recorded geo-coordinates. It focuses on the problem of predicting location state transitions. Position states for a user refer to a set of anchoring points/regions in space, and the prediction task produces a sequence of predicted location states for a given query time window [9]. If this problem can be solved accurately and efficiently, it may lead to new location based services (LBS) that can smartly recommend information to a user based on his current and future location states. The proposed iLoc (Incremental Location-State Acquisition and Prediction) framework solves the prediction problem by utilizing the sensor information provided by a user's mobile device. It incrementally learns the location states by constantly monitoring the signal environment of the mobile device. Further, the framework tightly integrates the learning and prediction modules, allowing iLoc to update location states continuously and predict future location-states at the same time [9].

Smart DC is a mobility prediction-based adaptive duty cycling for daily location monitoring. It has three main parts: mobility predictor, mobility learner, as well as adaptive duty cycling [1], [4]. It uses unsupervised learning to collect mobility patterns in colloquial conditions. In this there are three types of level such as the GSM, WIFI, and GPS to collect exact location details. These are the three types of sensing according to the sensor's energy consumption [4]. Location predictor use in mobility predictor to predict departure time to the next location. Therefore there are two types, Markov predictor as a location-dependent predictor, and nonlinear time series analysis as a location independent predictor. These are capable in accuracy with memory handling aspects in predictions for human mobility. Adaptive duty cycling uses a Markov decision process (MDP) to decide useful sensing moment for a given energy resources [4]. It is use for maximizing the accuracy of monitoring mobility, and to optimize a sensing rule on diverse smart phone handling with a given energy plan. It all together performed mobility learning and prediction, and superior in terms of accuracy and low energy utilizations. There are three main components in the system: mobility learner, mobility predictor, as well as adaptive duty cycling. The role of mobility learner is to collect individual mobility history without impending users. The basic idea is that fine-grained sensing is activated only if coarse-grained sensing fails to obtain accurate information. The role of mobility predictor is to estimate the reward function R based on action set A and transition probabilities P. In other words, when a user visits a place, the system makes prediction on stay duration in a place. The goal of adaptive duty cycling is to maximize the accuracy of monitoring mobility, and to optimize a sensing policy on diverse smart phone usage with a given energy budget [1]. Randomness is inherent in human movements although humans tend to move with reasonably small variation [4].

III. THE LOCP SYSTEM MODEL

The LocP system model is design is such a way that it always provides location tracking with adaptive duty cycle which provides less energy utilization. The explanation of work is as follows: First of all recognizing POI {point of interest} is a key objective of the system model, This location traces is then fetch in the predictor to predict the next location. Thus, we focus on monitoring meaningful places (i.e., points of interest, or POIs) using the regularity of individual mobility pattern. The main idea is that the system senses location context based on a predicted; that is, when the movement to the next location will take place and future position. Predicting the next location of a node based on the observations of his mobility activities over some phase of time and the up to date locations that he has visited. This model used an n-MMC model for next location prediction; figure 2 is the architecture diagram for the LocP system.

The key practical challenges are (1) instantaneous tracking and predicting a user's mobility, (2) adaptive duty cycling that is use because low energy consumption, (3) Fine grained location history (4) accuracy in prediction to the next position.

A. Problem Definition

Continuous location tracking with prediction of the future location is a fundamental resource for broad-domain applications. We address the issue of predicting the next location of an individual based on the observations of his mobility behavior over some period of time and the recent locations that has visited.

B. LocP System Architecture

The system consists of three main components: (1) Mobility Tracking, (2) Adaptive Duty Cycling, (3) MMC model for prediction the future position.

Mobility Tracking: The role of mobility tracker is to collect individual mobility history by continuous monitoring the user's movements with respect to places and paths. It uses GPS sensor for tracking raw co-ordinates. This stage activates the GPS to acquire fine location, adaptive duty cycle is use to avoid continuous use of GPS, rather than sampling of the GPS signals is done at particular interval. The user can assign meaningful place based on his interest and this place will be treated as POI in the Markov Chain Model.

Adaptive Duty Cycling: The goal of adaptive duty cycling is to maximize the accuracy of monitoring mobility, and to optimize a sensing policy on diverse smart phone usage with a given energy budget. Mobile user does not always follow the previously-observed movement patterns. Thus, the accuracy of the prediction-based adaptive duty cycling may decrease due to the randomness of human behavior. Therefore we split a given energy budget E into two parts: energy for prediction E_{PRD} (i.e., the case of following patterns in mobility history), and energy for exception E_{EXP} (i.e., the case of moving with a new pattern). To split E, we make use of potential predictability in individual mobility. The system automatically measures predictability by comparing the current pattern with the historical data. For example, potential predictability is 0.8 if a user follows the previously observed pattern 8 times out of a total of 10 visit counts. Then, the exception ratio is 0.2 and the system allocates 20% of given energy for monitoring exception.

Mobility Markov Chain (MMC) Models: It models the mobility behavior of an individual as a discrete stochastic process in which the probability of moving to a state (I.e. POI) depends only on the previous visited state and the probability distribution of the transitions between states which is explained in algorithm 1.

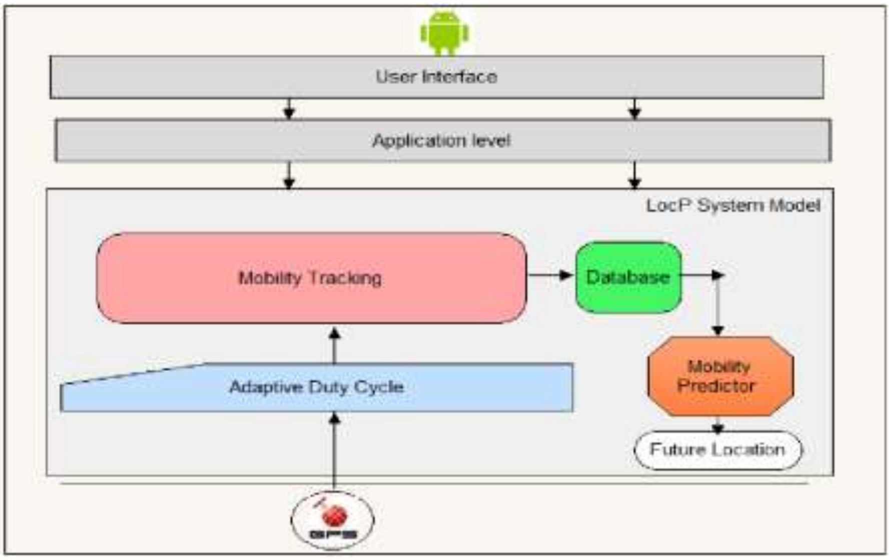

Fig. 2. Architecture Diagram of LocP system

Algorithm 1: Mobility Markov Chain Formation Algorithm

Input: a trail of (mobility) traces D, n the number of previous location kept, *R* the radius of a cluster. -Preprocess the trail of mobility traces D by deleting thus producing D'.

-Run a clustering algorithm on D' to discover the most significant clusters.

-Merge the clusters that share at least a common point. -Merge the clusters that are within d. min distance of each other

-Let *list*POIs be the list of all constructed clusters.

-for each cluster C in *list*POIs *do*

-Compute the cluster C in terms of POI

-end for

-Sort the clusters in *list*POIs

-for each cluster Ci in *list*POIs do

-Create the corresponding state pi in the mobility Markov chain -end for

- do

-Update the n -1 previous locations (FIFO) and the current position with Ci

-Label the trace m with the n-1 previous locations and Ci

-else

-Delete all traces that are “unknown”

-Compute all the transition probabilities for predicting the future position between each pair of states of the Markov chain

-return the Mobility Markov chain computed

C. Advantages of Proposed Framework

- Novel algorithms for prediction.
- n-MMC mobility model is used for future location.
- It is implemented on android framework.
- The approach minimized the energy consumption which involves more energy backup.
- Acts as a building block toward expanding the domain of mobility services.
- Accuracy in prediction is in the range of 65 to 85 percent on real dataset.

IV. EXPERIMENTAL EVALUATION

In these experiments, we used three different datasets, whose characteristics are summarization are shown in table 2 which are the important parameters for prediction purpose. The LifeMap dataset is collected by Yonsei University for about 1 year which consists of user mobility data and the LocP system dataset is summarized in the table 2. In order to assess the efficiency of the system, we compute two metrics: the accuracy and the energy. The accuracy Acc is the ratio between the numbers of correct predictions $\square_{\text{correct}}$ over the total number of predictions $\square_{\text{total.}}$

Accuracy =□□correct/□□total

In our experiments, we split each trail of mobility traces into two sets of same size: the training set, which is used to build the n-MMC, and the testing set, which is used to evaluate the accuracy of the predictor. As expected, the accuracy first improves as n increases but then seems to stabilize or even decrease slightly as soon as n > 5, for the LifeMap dataset.

Moreover, the prediction accuracy is usually better on the training set that on the testing set, this difference is not significance for this refer figure 3 which demonstrates the pre

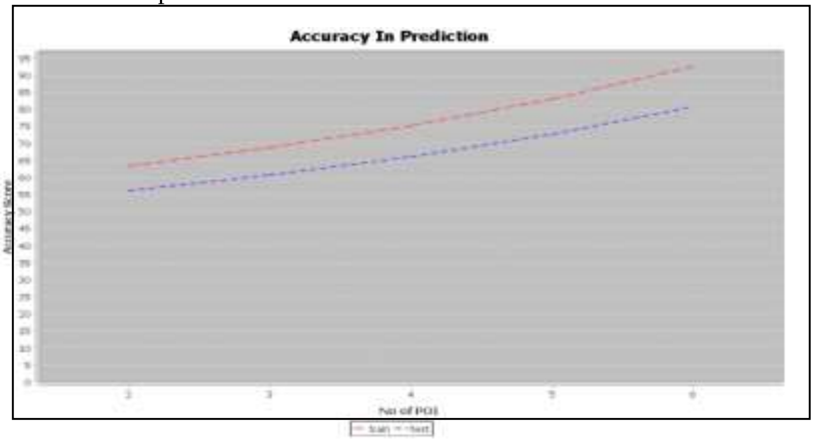

Fig. 3. Accuracy measure for a single user for real dataset

-diction considering the number of previous positions. This is the graph showing the accuracy in prediction on LocP system dataset. In the above graph, the X-axis represents the number of POI, and Y-axis represents the accuracy score for the dataset. This means accuracy goes on increasing with the POI for a three months dataset. This is because the dataset is a fine grain mobility history.

We also examine the cost and performance of prediction based adaptive duty cycling. We had study the sensitivity of parameters and the effectiveness of the prediction technique. We then show the energy consumption and accuracy of the overall system.

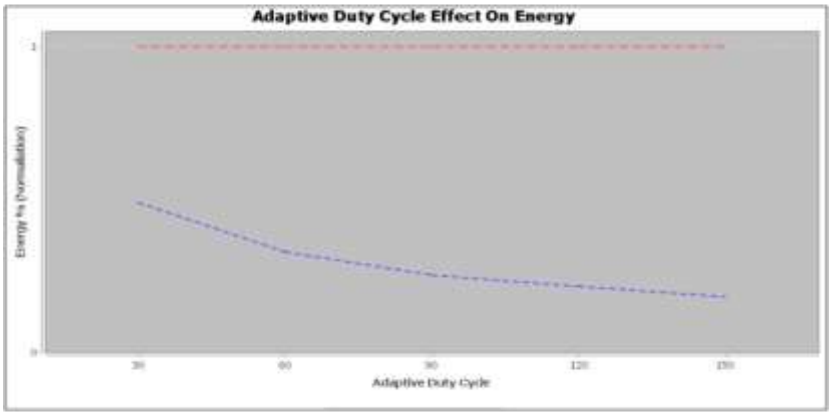

Fig. 4. Effect of Adaptive Duty Cycle on Energy Consumption

In the figure 4 graph showing the effect of adaptive duty cycle effect on energy consumption. In the graph, the X-axis represents the number of cycles, and Y-axis represents the energy consumption which is normalized. The graphs show the comparison of two systems. This means that for a system with adaptive duty cycle, it reduces energy consumption with the increasing of the cycles.

V. RESULT

The data sets consist of real traces from one to two users. The proposed system runs in a background service which routinely gather the user's mobility and to outline sensor usage time. This refined mobility history will be used for the prediction process. For accurate prediction fine grained mobility history is essential, predicted result will be the future position. Table 2 gives the example of the location trace history of the mobile user.

TABLE II. MOBILITY HISTORY SUMMARIZATION

POI {Point of interest}	**Description**			
	Latitude	***Longitude***	***Speed***	***Time***
Chowk	18.52691	73.84237	4.357	2014-07-04T09:22:10.935Z
Moden College	18.52624	73.84642	7.328	2014-07-04T09:23:14.947Z
Hospital	18.52429	73.8492	6.563	2014-07-04T09:24:23.942Z
State bank	18.51522	73.84228	0.485	2014-07-04T09:27:11.979Z

This mobility history provides meaningful places with its raw co-ordinates in terms of latitudes and longitudes with respect to time.

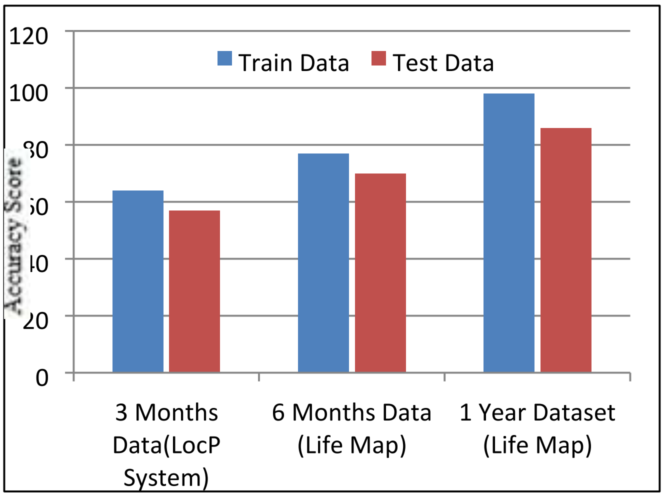

Fig. 5. Prediction Accuracy for Different Dataset

The figure 5 shows the graph, the X-axis represents the amount of dataset which are fined grain mobility history, and Y-axis represents the accuracy score for different datasets. This means that accuracy in prediction increases with the increasing amount of dataset. We have shown the prediction accuracy for different dataset, one is the self-user collected data and another is the LifeMap mobility dataset. This is demonstrated for n=2 i.e. considering the previous two position for prediction.

VI. CONCLUSION AND FUTURE WORK

Mobility prediction, which is estimating the future positions of the mobile nodes in mobile Adhoc networks, entirely influences the service-oriented as well as the application oriented characteristic of MANET's networks. This system model has resolved the problem of continuous location tracking with the low energy utilization in actual deployments. This demonstrates that this approach will not only reduce the energy utilization in mobile phones but also improves the accuracy in prediction. As a result the proposed model is a well-known mobility prediction design, with low energy utilization and this approach to mobility prediction is new in the area of mobile Adhoc networking. Further issues will be using the speed between the two meaningful places can be used to calculate the stability time for that place i.e. how much time the mobile user is going to be present at that location.

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