Analysis of Predictive Algorithms using Mobile Call Traces

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Abstract: The next generation of access technology will ensure wireless connectivity to any one at almost any location using wireless access technology. While Mobile IP is an established technology and is a macro mobility technology, Cellular IP is a sub-division of this and is known as a micro mobility technology. With device portability the communication device moves, with or without the user. Many mechanisms in the network and inside the device have to make sure that communication is still possible while it is moving. Apart from signaling across the wired network, resources have to be employed to accurately track the mobile user. This tracking of the user is inefficient in terms of bandwidth and power consumption. A number of movement prediction methods to alleviate this problem have been proposed for cellular networks. In this paper we will examine some of these and compare them using actual historical mobile call trace data.

1 Introduction

Although Mobile IP is a powerful Internet mobility protocol that scales reasonably with the number of users in a network, it presents some weaknesses for frequently migrating hosts. Specifically, after each host migration, a local temporary address must be obtained and communicated to a possibly distant home agent. This significantly disturbs TCP connections while causing network-signaling overload. The simplest way to alleviate this weakness is to introduce hierarchies into the IP mobility infrastructure. A hierarchical IP mobility management scheme specifies that host mobility should be handled where it originates, namely in the access network. Recent initiatives in the IETF focus on standardizing some micro-mobility protocols that will support IP mobility in an access network, while inter-working with Mobile IP in a hierarchical way in order to support wide area mobility. Cellular IP is such an approach, which combines the efficiency and scalability of IP with inherent features found in cellular networks, such as seamless handoff support, passive connectivity and paging as proposed by Valko et al [1]. There are many approaches when it comes to solving the handover issue in traditional cellular networks. One method is to predict potential future cells to reserve resources and forward data to the right base station (BS) prior to the arrival of a Mobile Host. Although predictive approaches have been used for ATM wireless networks for a long time only recently has this method been considered for cellular networks of the 2nd

as well as 3rd Generation. This paper aims to provide an examination of current predictive handover approaches, using historical mobile user movement data, and propose some additional parameters that can improve prediction accuracy ratio in a micro-cellular environment.

2 Predictive Methods for Mobile Movement

The frequently used assumptions described by many papers on movement predictions focus on the physical movements of users as outlined by Bauer [2]. These do not really pay attention to user mobility from the perspective of a wireless network. What is required in a wireless system is for the mobility prediction scheme to predict the network access point through which the mobile user will connect to the network, i.e. the cell/base station to which the user will next connect. In an ideal environment the handover would be to the closest base station. However base station overloading and anomalous propagation effects frequently result in handovers to base stations other than those adjacent to the current cell. Handover methods adopting predictive approaches is mostly based on forecasting potential future BS's using mobility patterns and probabilistic predictions.[3] They rely on the majority of users following movement patterns that can be predicted with reasonable accuracy. In order to perform this task the system requires information on the cells individual MH's have visited in the past. However this information has to be collected over a sufficiently long period of time to reflect user behavior. The following section briefly outlines some predictive methods for handover.

2.1 Location Criterion

A Mobile Terminal (MT) starts recording the next BS as soon as a MT leaves its location at that time and it also works to track the number of times it's visiting each of the BS's. So a probability distribution of next moves is formed with the help of this mobility history information and the distribution of each departure is referred to as departure history. So this algorithm predicts the next move of the MT by the use of the departure history of this location and by the identification of the present location of the MT. The most visited BS will be predicted as the next BS. [4]

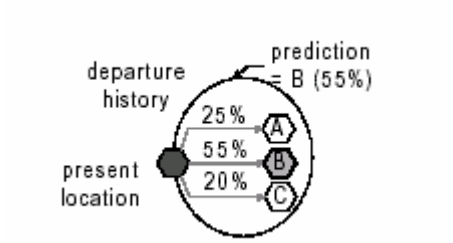

Fig 2.1 Location Criterion Algorithm

2.2 Direction Criterion

If the direction of travel of the MT is taken into account then the accuracy can be improved. This happens when its previous and present locations are known. This algorithm includes direction information with the history of departure. It predicts the next move of MT with the help of the present direction of travel of the MT and the departure history of this direction. It predicts the next BS by the use of the move that has highest departure rate.

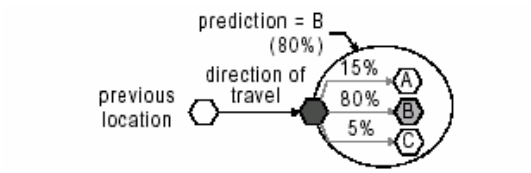

Fig 2.2 Direction Criterion Algorithm

2.5 Adaptive User Mobility Prediction Algorithm

This algorithm proposes to limit the reservation and configuration procedure to a subset of cells around the user. The viability and effectiveness of the proposed scheme is then demonstrated through a simulation based on measured data. If the movement of

a user is known, the reservation and configuration procedure can be limited to the regions of a network a user is likely to visit. To determine a user's movement patterns in wireless mobile networks, the base station ID that a mobile user was connected to was logged as a user drove between the central business districts of a city to one of its outer suburbs. All inbound and outbound trips followed the same highway and were repeated during office hours for five days. Most mobility modeling schemes in the literature would consider this to be a one-dimensional handover issue. That is, the movement traces of this user should indicate either a track or circle pattern with high tendency of re-occurrence during each trip. [5]

2.5.1 Differences between Actual Call Traces and Conventional Mobility Models

It was shown that large proportion (30% - 95%) of handover events have excessive variance compared to the ideal forward-backward model. By comparing the inbound and outbound movement traces separately, it was found that most "random components" of the traces came from the Ping-Pong effect between adjacent base stations or some temporary handovers to other base stations relatively far apart (i.e. not neighboring base stations). The authors believe that the above effects are caused as a result of a combination of signal fluctuations, constraints of the surroundings, congested cells, and moving obstacles. A simple example of the differences between the user mobility patterns and the user behavioral patterns are illustrated in Figure 2.5

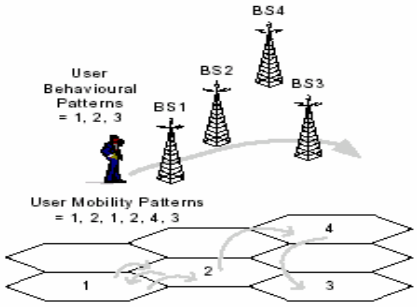

Fig 2.5 Differences between user behavior patterns and user mobility patterns

The use of conventional prediction algorithms were found to be inaccurate when traffic patters such as outlined above was presented. The adaptive user mobility prediction algorithm is defined as follows: A prediction is derived from a probability distribution of all possible next moves. If the first predicted cell does not contain a probability higher than the Prediction Confidence Ratio (PCR), one or more extra cells will be added to the group of cells in which resources will be reserved in advance and services will be pre-configured. This process will continue until the sum of their probabilities exceeds the PCR. Applying various PCR values to the prediction of cellular call traces, a high prediction accuracy rate has been obtained.

3 Limitations of Individual Movement History

The schemes that rely on individual mobility patterns have three limitations. Change of user behavior is concerned with the first. The overall probability distribution cannot be affected significantly due to a recent change of the behavior of the user because the mobility history can be logged for a long time. The second limitation takes place when a mobile terminal visits such places that were not visited in the past so no past history is available for the probability calculation. The third limitation is concerned with the actual channel allocation availability at the base stations and other factors such as signal impediment due in the immediate area surrounding the user. This latter limitation is demonstrated by Chan with his Adaptive Prediction Algorithm proposal above

4 Movement Trace Analysis

Stanford University has provided the wireless community with movement traces for use in defining movement algorithms.

SUMATRA is a trace generator that encompasses several calling and mobility models. The unique aspect of SUMATRA is that it is well-validated against real data on calling and mobility traces that Stanford research group has obtained. By releasing the user calling and mobility traces from SUMATRA, it is hoped to provide a common benchmark in which researchers can directly exchange performance results, and avoid inaccuracies. We used mobile activity traces from SUMATRA in our research project. We analyzed the call traces and using two of the above algorithms to provide a prediction accuracy ratio [7].

4.1 Actual Call Traces Used

Using the movement data as shown in table 4.1 below, we analyzed a total of 4,239,053 calls for the twenty four hour trace output. We examined the movement file. Having also a map of the zones, i.e., what zones were contiguous, geographical location, we analyzed movement based on two criteria i.e., location of user and direction of user.

Trace Duration	24 Hours
Number of Zones	90
Users per Zone	1100
Calls per Hour	2
Call Duration	3 Minutes
Moves per Hour	0.3
Move Duration	20 Minutes
Zone Configuration	San Francisco Bay Area
Callee Distribution	80% Local 20%Random
Destination Distribution	Multi-Zone Distance

Table 4.1 Sample Data Input Used

4.2 Location of User

The results obtained in our analysis, based on this criterion were remarkably close to that outlined by Chan [4]. The output as shown in Figure 4.2 shows a 2% difference in prediction of next Base Station.

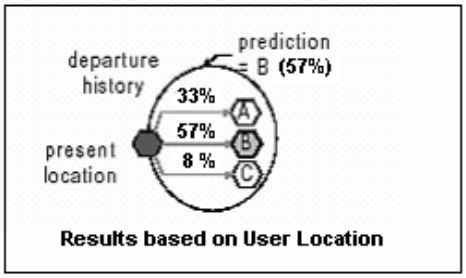

Table 4.2 Location Prediction based on Present Location

Our results show a 57% chance that the user will move to Station B, with a 33% chance that the user will choose Station A. The Location Criteria is based on the fact that Station B is the nearest location to the previous position of the user. Geographical factors are also taken into considerations. The user will have to travel a pre-defined route to get to Station B.

4.3 Movement Direction of User

The results obtained in our analysis varied somewhat to that outlined by Chan [4]. The output as shown in Figure 4.3 below shows a 10% difference in prediction of next Base Station, based on user movement direction. Our results show a 70% prediction to next base station based on knowledge of user movement. The second choice base station has a slightly higher prediction of 20%, which challenges the accuracy of Chan's figures, based on this movement criterion.

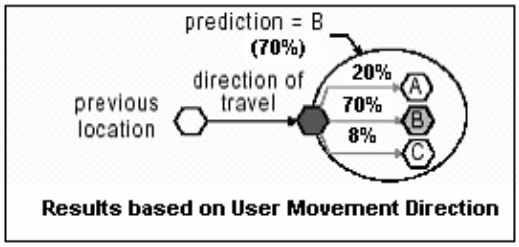

Table 4.3 Location Prediction based on Movement Direction

Using these call traces we have examined just two algorithms for path prediction as outlined above. This work is ongoing and is reflected in the content of this paper which

has looked briefly at just the main movement prediction schemes.

5 Conclusion and Future Work

There are many problems with existing methods with a lack of accuracy in the prediction of future movement. Some of the more complex algorithms suffer from an excessive processing overhead, which renders them untenable as practical solutions. Such schemes lack the combination of simplicity and effectiveness needed to support future mobile developments, such as Cellular IP. The latter algorithm examined, as proposed by Chan et al (1999), shows clearly that there is a large discrepancy between the user mobility models that have been reported in the literature and actual system movements.

The search for efficient paradigms for prediction is an ongoing one, for which the use of adaptive learning methodologies, offers a possible development path for Cellular IP movement prediction. The advantages of such an approach are obvious – the long term nature of cellular networks lends itself to adaptive learning, the group mobility of users can provide a realistic data set on which to calculate predicted paths. With Cellular IP, the issue of rapidity of handover is about to assume critical importance for the successful deployment of such systems within the user space.

Many investigations into user movement prediction in relation to micro-mobility technology is being carried out using the well established Network Simulator 2 (NS2) , a tool that produces a movement pattern using the random way-point algorithm [6]. Random user movements are thus generated. This random movement is then used as a reference base from where other movement patterns can be compared to. Random movement only accounts for a small percentage of user movement. Results have shown that historical data is the most reliable method of future movement prediction. In this paper we have used such historical data to analyze future user movement prediction based on two movement prediction algorithms.

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