A New Routing Area Displacement Prediction for Location-Based Services based on an Enhanced Ant Colony

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***Abstract*—In Location-Based Services (LBSs), the service is provided based on the users' locations through location determination and mobility anticipation. Most of the current location prediction research focuses on generalised location models, where the geographic extent is divided into regular shape cells. One such technique is the Mobility Prediction based on an Ant System (MPAS), which depends on the earlier Ant Colony Optimisation (ACO) that suffers from problems such as search stagnation and pheromone update. In this paper, a New Routing Area Displacement Prediction (NRADP) is introduced, which works on the routing-area level instead of the cell level. Experimental results show that the NRADP offers improved effectiveness, higher prediction rate, and a reduced search stagnation ratio in comparison with the MPAS.**

***Index Terms*—Ant Colony Optimisation, LBSs, Mobility Prediction, Cellular Network, UMTS, Routing Area.**

I. Introduction

Cellular networks have become a platform for leading-edge Internet services, for instance a person can solve problems in any place without any need to go to his or her office or to travel, just by using his mobile phone or laptop. These services include both common voice services as well as multimedia and integrated data services. Integration of the Internet Protocol (IP) with Third-Generation (3G) wireless communication through the Universal Mobile Telecommunications System (UMTS) All-IP network was proposed by the Third-Generation Partnership Project (3GPP) as the next generation of telecommunications networks.

However, these networks are facing problems such as fragile wireless links, resource consumption, and denial of services and mobility of Mobile Users (MUs). The mobility location is changing during the constantly movement of MUs. The cellular communications network is divided into cells, where each cell covers a specific area within the network. The cell contains a Base Station (BS) with responsibility for communications with MUs residing in the cell. Several cells that are grouped together belong to Routing Area (RA). Consequently, the network consists a set of RAs. If the MU is at the boundary of either cell or RA and is going to different one, the handover occurs and the connection in some cases will be lost because there are no resources to handle the MU at the new serving area. In contrast, if the resources are enough at the new serving area often the connection is lost because the time between the MU sending a request message for re-location and arrival in the new area is insufficient to finish the handover procedure, especially if the RA is re-located. Finally, if the connection is not lost during the handover, a service is not delivered in time to the MUs.

If the network has enough information about mobile users and neighbourhoods, appropriate artificial intelligence systems are employed. These help the network to predict the next displacement for MU with high accuracy, then resource will be saved, delay time for delivering the services will decrease and improve the network functionality such as paging, location update and handover.

The NRADP is proposed in this paper to improve the mobility prediction for Location-Based Services and the MU's displacement prediction is achieved by the developed ACO. NRADP works on the RA, that means every RA classify as independent colony and control their own. Variables pass through them because each one of them needs to know the visibility of his neighbours.

The main contribution of this paper targets the LBSs cost by deploying a prediction technique on the RA level that allows intelligent LBSs disclosing and hence minimises the computation cost, consumption of resources, reduces the message passing and the overall cost of the location management process such as location update. NRADP scheme utilises geometrical and topological techniques allowing users to receive their desired services timely fashion.

The rest of the paper is organised as follows: Section 2 discusses the previous work on mobility prediction for LBSs and their limitations are described. The cellular communications network environment is discussed in section 3, proposed technique is introduced in section 4 and its simulation model and result analysis is presented in section 5. Finally, the conclusion and future work is presented in sections 6.

II. Previous Work

Locating users as they move from one place to another in a cellular computing environment is the key to providing continuous services with unrestricted mobility. Therefore, the data management in this environment presents challenges for the need to process information during the move, to cope with resource limitations and to deal with heterogeneity. One of the applications of cellular data management is LBSs which have been identified as one of the most promising areas of research and development [1].

Strategies of location management in cellular environments can be classified into static and dynamic. In the static strategy, the updating operation is reduced according to the network topology. This technique suffers some inefficiency especially for users that are located around the RA boundaries and who cross these boundaries repeatedly. Moreover, RA sizes are fixed for all MUs as specified by the cellular infrastructure, without considering their individual mobility and service request pattern.

Dynamic location updates have been developed to address and enhance the efficiency of the static strategy [2]. The updating operation is initiated according to the MU's movement pattern and the frequency of its requesting service. Location is among the most important contextual pieces of information for mobile applications. Much of the previous work on LBSs treated location as an additional attribute of the data tables [3]. In this way, LBS queries can be processed like ordinary queries except with additional constraints on the location attribute. Predictive location was dynamically introduced to predict a MU's future location based on the current location information, the user's historical mobility pattern and the auxiliary information. Therefore, the mobility realisation and location determination are two factors in location prediction to determine the location of a MU at a time t.

Francois and Leduc [4] introduced the accuracy of prediction to evaluate models. Numerous prediction models were introduced to increase the accuracy of the prediction techniques for users with varying speed that was reported in the literature. However, none of them can fulfil the optimal accuracy prediction rate and effective cost requirements.

In the cell techniques [5], [6] a service area is partitioned into several cells; the cell covering the MU will page his or her device to establish a radio link in order to track the changes in the location of MUs.

The cells broadcast their identities and the MU periodically listens to the broadcast cell identity and compares it with the cell identity stored in its buffer. If the comparison indicates that the location has been changed then the MU sends a location update message to the network [7].

Prediction techniques that are based on a cell technique can be enhanced by heuristic methods and neural networks [8], [9]. Liou and Lu [8] divided the cell into two areas, edge and non-edge. The edge areas have neighbouring cells, while the remaining areas are considered as non-edge areas. When the MU is in a cell's edge area, the information is passed to a neural network which predicts, from the neighbour's cells, the next cell that will be visited. Another technique captures some of the MU activity and paths. These paths are progressively recorded, giving a history record which is used as an input to a neural network to predict the next cell that will be visited [9].

The techniques proposed in [8], [9] suffered from a long training phase on mobile movements data which are used to build a knowledge base before making predictions. Therefore, the MU may change his or her activity, such as movement pattern or visiting a location he/she has never visited before, thereby bringing new cases which the techniques have not encountered in training. Hence, the prediction percentages dramatically decrease.

The first ACO algorithm, was an Ant System (AS)[10], [11], [12], [13], proposed by Dorigo et al. to solve the Traveling Salesman Problem (TSP) [10]. They proposed a new model of combinative stochastic optimisation, based on the ants' behavior, inspired from [14], [15], [16]. This model is useful when used with greedy heuristics to find acceptable results at the early processing stages. Complex systems need to use distributed computational to deal with the random space variable, thereby avoiding premature convergence.

Recent research on ACO focuses on premature convergence of the pheromone that the search concentrates at early state of search, which negatively affects on the performance of ACO. It will lead to premature stagnation of the search. Search stagnation is proposed in [10] as the situation where all ants follow the same path which is generated by other ants and construct the same path over and over again. In a sense, no new paths will be found anymore.

In order to improve the performance and reduce the computation cost, the relation between solution feature and the distance from good quality or optimal solution must be addressed [17], [18]. To avoid premature convergence and improve the overall performance, the MAX-MIN Ant System (MMAS)[19], [20] and Pheromone Trail Centralisation (PTC) [21], [22] are also proposed.

The techniques that are introduced in [23], [24], [25] are still based on cell mobility prediction. The smallest service area will then be presented by the cell. Heterogeneous and homogenous network prediction mechanisms were discussed in [25]. The main drawback of this technique was an extra overhead added to the network and lack of security. In [23], [24], the techniques which are based on temporal attribute to enhance the prediction rate used closed sample, small region and restricted environment such as university urban. A long training phase was required for [24]. The neighbours' history was not utilised and the fast mobile reaction for unexceptional mobility habits was not handled.

MPAS in [23] used the version of ACO that has been introduced in [10]. The service area represented by Micro and Pico cell, and cell division was not used.

The segments of a highway that connect a student or employees' accommodation and a university campus together are covered by a cell in MPAS. The MPAS prediction process is based on the user's usual habits such as the students who leave the accommodation during working days to go to the university and at weekends he or she goes to the stadium instead of the university. If a new user enters the network, the MPAS prediction handled the MU according to his/her neighbours' histories. The history of each MU during days was memorised in the BS for each cell through a special architecture called the history table. Updating and processing the history table is handled periodically.

MPAS modelled MU displacements by ant colony going from current cell forward to one of the neighbour's cells searching for food. When a MU enters a new cell, the MPAS predictor is started. It creates a movement table with 50 entries. This table is fed by entries from the history table with same source and destination cell and the date for the same mobile identification. The rest of the entries of the movement table will be fed by other MU's history; for more details on movement table and precise mechanism for feeding see [23]. Moreover, each displacement prediction process for each MU needs to create a movement table to complete the prediction process. When the prediction process is finished, the MPAS will destroy the movement table that is related to such prediction displacement.

The MPAS creates a colony of ants for which the members have the same number of entries in the movement table. Each ant has a number according to the movement table i.e. ant1, ant2, ant3 or ant50. Each ant is associated with two variables, pheromone and visibility. The next cell displacement will be calculated after the pheromone and visibility manipulations [23].

The authors in [26] introduced a new Splitting-based Displacement Prediction Approach for Location-Based Services (SDPA). The model reduced the service area to be less than the cell. However, this model deals with static splitting which means that SDPA can split cell into a static number of regions.

SDPA [26], [27] has been developed to improve prediction rates and minimise consumption of resources and the overall cost of the location management process compared with PLM. Also, the SDPA reduces the service area and the number of predicted routes during the MU trip by dividing the cell into eight equivalent regions. Thus, the SDPA approach improved the location prediction probability over PLM. The average complexity that is required for usage space is smaller than the PLM approach. In addition, these techniques still work on the cell level which is more expensive in terms of message passing and execution time because the SDPA and PLM are executed in a tight time slot. Both of them work at cell level. Moreover, SDPA is based on a static algorithm for reducing the service area into small regions instead of a cell. This was considered as another drawback.

III. Prediction Framework for NRADP

The UMTS is one of the new 'third generation' (3G) mobile cellular communication systems being developed within the framework defined by the International Telecommunication Union (ITU) and known as IMT-2000. UMTS aims to provide a broadband, packet-based service for transmitting video, text, digitised voice, and multimedia at data rates of up to 2 megabits per second while remaining cost effective.

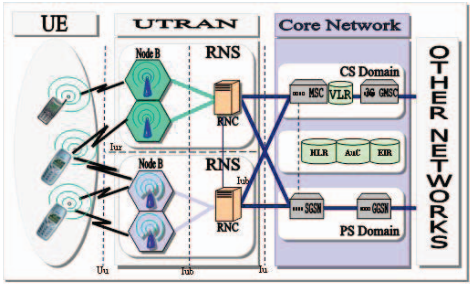

Fig. 1. UMTS Architecture.

In order to demonstrate the architecture of a UMTS network, the elements of a network are introduced as the architecture of UMTS. Figure 1 illustrates the UMTS's architecture. UMTS is divided into three major parts: the air interface, the UMTS Terrestrial Radio Access Network (UTRAN), and the UMTS core network. The base stations and the Radio Network Controllers (RNCs) are collectively known as the UTRAN. From the UTRAN to the core network, the RNC will decide to where the traffic will be transmitted. Packet traffic is sent to a Serving GPRS Support Node (SGSN), and then to the Gateway GPRS Support Node (GGSN). The functions of the GGSN are very similar to the normal IP gateway, which transfers the received packets to the appropriate Internet address. On the other hand, if there is a voice call from a subscriber, the RNC will transmit the traffic to the Mobile Switching Center (MSC). If the subscriber is already authenticated, the MSC switches the phone call to another MSC (if the call is to another mobile subscriber), otherwise the call will be switched to the Gateway MSC (GMSC) (if the call is to the public fixed phone network) [28], [29].

IV. NRADP Technique

This section presents a NRADP. This technique is based on a third generation mobile network, such as UMTS.

A. *NRADP Principles*

The NRADP is based on the responsibility of the RA component instead of using the MU or cell. This helps avoid the computation power required at MUs, since power and resource limitations are obstacles for mobile manufacturing.

The SGSN is managing the RA, where each RA contains one or more cells based on the radio specifications and geographical features, as shown in figure 2.

The SGSN is responsible for managing and updating the history displacements for all resident MUs. Moreover, it handles the NRADP technique to predict the next displacement for the MU according to the current location, history displacements and visibility to surrounding neighbours.

When a MU enters the network, the SGSN uses the MU's and his/her neighbours' histories to make a relation between them. Thus, the prediction percentage and handling of any unusual movement is enhanced. In contrast, if the SGSN does not contain the history displacements for the MU, it should use the history of its neighbours.

Each RA is modelled by a colony and each MU is modelled by an ant. An ant goes from the current RA to a neighbouring RA looking for food. In the food searching, the ant prefers to go through the usual paths or according to the displacement of its neighbours.

B. NRADP Prediction

When a registration to the network is made for a MU, the SGSN creates an ant to represent the MU. Whilst moving, the ant will deposit a pheromone on RA, which would be considered as the communication channel between all ants in the cellular communications network.

At the first entrance of MUs to the network, no pheromone would be found from any neighbour, which is why the movement goes randomly. Over time, each RA has its pheromone which guides MUs to the most preferable RA for the future displacement.

Finding the probability of each RA, the previous MU's visibilities and the intensities of the pheromones for all adjacent neighbours are required. Suppose that *Ph* is a vector of pheromone from 1 to *A*, where *A* stands for the number of adjacent RAs. The probability for the MU from current RA C_{RA}-*th* to *j* RA is expressed in equation 1.

$$P_{C_{RAi,j}}(t) = \frac{[\tau_{C_{RAij}}(t)]^{\alpha} * [V_{allC_{RA}ij}(t)]^{\beta}}{\sum\limits_{u \in Ph_A(i)} [\tau_{iu}(t)]^{\alpha} * [V_{all_{iu}}(t)]^{\beta}} \tag{1}$$

where$P_{C_{RAi,j}}$ is the probability of the MU at RA *i* at time *t* to RA *j* , *t* is the time factor, τ is the pheromone level and V_{all} is the visibility -memorisation- of the MU. The visibility here, V_{all}, is obtained from the combination between local and global visibility, according to equation 2.

$$V_{all} = P * V_L + (1 - P) * V_G \tag{2}$$

where *P* between 0 and 1, V_L is the local visibility and V_G is the global visibility.

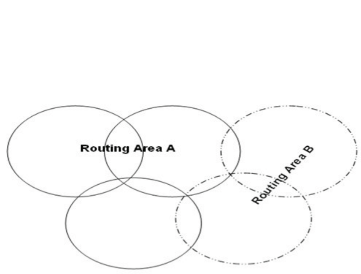

Fig. 2. Routing Area Coverage.

Memorisation entity is used to calculate the visibility variable *(V)*, which is represented by a vector *(n)* and its length based on the number of adjacent RAs A_{RA}. An element of this vector either locally or globally represents the ant visibility of an adjacent RA. In a sense, the local memorisation reflects the MU's behaviour.

When a hard handover occurs for a MU, the MU changes the RA to another one. At this time, the MU deposits its pheromone on the RA which has just been left. The amount of pheromones is deposited on each RA represented by equation 3.

$$\Delta\tau_{i,j} = \begin{cases} \lambda * Q * \tau_{staying\_in} & \text{if } \lambda * Q * \tau_{staying\_in} < Q \\ Q & \text{if } \lambda * Q * \tau_{staying\_in} >= Q \end{cases} \tag{3}$$

where $\Delta\ \tau_{i,j}$ is the pheromone quantity that would be laid down on the RA by the MU when it left RA *i* to RA *j*. *Q* is a constant which represents the maximum quantity of pheromone that would be laid on each RA. The value of *Q* is greater than zero > 0. $\tau_{staying\_in}$ is the time that has been spent by the MU in RA *i*, λ is a constant fraction which value is $0 < \lambda < 1$. λ is used to prevent the pheromone amount that has been laid from exceeding the *Q* value since this amount increases proportionally over the time.

When the value of $\Delta\ \tau_{i,j}$ is less than *Q*, the MU's pheromone affects the pheromones that are held by the RA in proportion to the time spent in that RA. If $\Delta\ \tau_{i,j}$ is greater than or equal to *Q*, the MU spends a very long time in the RA, which means that the MU is working or living there. This leads to a pheromone quantity greater than *Q*, therefore the quantity laid down is entirely *Q*, to avoid a bias of the quantity that may be laid down and stagnation of search.

Probabilities of all RAs that surround the RA where the MU resides in are calculated in equation 1, the highest probability should be taken into consideration as the next RA that the MU will visit. Hence, the next displacement is expressed in equation 4.

$$Next_{RA} = \max(P_{C_{RAi,j}}(t)) \tag{4}$$

$Next_{RA}$ is the next displacement.

V. Discussion of Simulation and Analysis of Results

A. Parameter Setup and Environment

Any cellular network simulation needs to be done over a very large coverage area. That is why the parameter setup uses the parameter assumption, as described in previous research and standardised over the 3GPP specification [30], [31], as shown in table I.

The simulations are done on Pentium IV computers with 2 GB RAM and CPU speed of 3 GHz. The operating system used was Windows XP, where the LAN speed was 100 Mbps.

A simulator was created using the Java programming language for the NRADP, in which the algorithm based on the developed ant colony model is implemented and tested. Each

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Number of cells	100
Cell radius	250 m
Transmission Rate	8 Mbps
Simulation time	18000 s
Iterations	10
Pause time	20 s
Velocity of UE	
Slow Pedestrian	5.6 k/h
Fast Pedestrian	11.2 k/h
Slow Vehicle	44.8 k/h
Fast Vehicle	89.6 k/h

experiment consisted of 10 different iterations to improve accuracy. Each experiment took five hours, as shown in table I.

The used ant colony parameters have been chosen according to [32]. The highest prediction rate they achieved was when the value of ρ was between 0.6 and 0.8, in this range the value of ρ was large enough to evaporate the pheromone. The best amount of initial pheromone to be laid down was 1 unit. The use of small amount of initial pheromone would save computation. To achieve balancing between local and global visibility, P was set to 0.6. The values of Alpha α should be chosen to be equal to values of Beta β to achieve better prediction rates [32].

B. Experiments and Analysis of Results

Corresponding to the prediction performance analysis, two phases of experiments were designed to evaluate the proposed technique. In Phase-1, experiments evaluated the prediction accuracy for each mobile user, which is the ratio between the number of correct predictions and the total number of predictions [4]. Phase-2 tested the prediction rate for 10 mobile users over time.

In phase 1, the prediction rate for each MU is tested over time. Figure 3 shows the prediction rate for 10 MUs which use the MPAS and NRADP techniques. According to this figure, the highest prediction rate for NRADP was 89% and the lowest was 48%, while it was 66% and 36% for MPAS respectively; where the highest prediction rate was related to the number of RA displacements. The highest number of displacements was the lowest prediction rate.

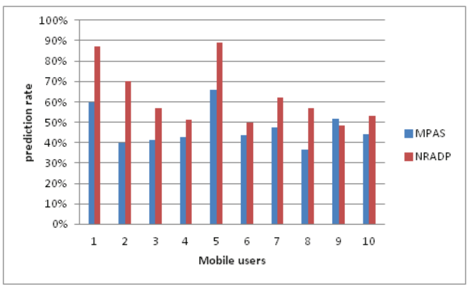

Fig. 3. prediction performance for MPAS and NRADP techniques for each mobile user.

There are many factors that affect the prediction rate, including the number of routing displacements, search stagnation, and previous knowledge of the MUs' behaviour in the surrounding regions. The routing displacement is affected by the number of areas that will be discovered. The core network consists of RAs which, in turn, consist of at least two cells. The MPAS technique depends on the probability calculation at the cell level, while NRADP works on the RA level. Thus, the number of displacements for NRADP will be less than that for MPAS. Consequently NRADP shows better prediction results than MPAS. In addition, the search stagnation is handled only by NRADP which aids in discovering new paths that represents better solutions for MUs. NRADP also reduces the blindness of a MU. The MU does not follow the previous discovered paths by other MUs. Therefore, the prediction rate is enhanced. It is, on average, 62% for NRADP and 47% for MPAS.

In Phase 2, the average of prediction rate for 10 MUs is obtained. Figure 4 depicts the prediction rate, over time, for both techniques. Each point in the figure represents the average prediction rate for 10 MUs. As can be seen, the overall prediction rate for NRADP is better than that for MPAS. It can also be noted the NRADP has less regression compared to MPAS, i.e. the NRADP prediction rate is more stable than that for MPAS.

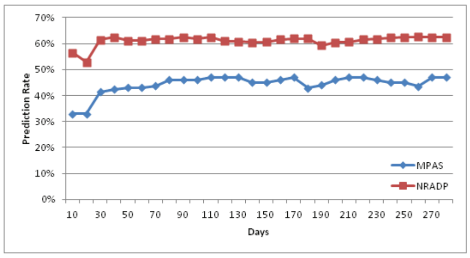

Fig. 4. The MPAS and NRADP prediction rate for 10 mobile users over time.

It was stated earlier that the prediction rate was affected by many factors. The fourth factor is the weight of pheromone and visibility. The ACO method was improved to be used in NRADP. The optimisation method depends on two factors, pheromone and visibility with two different weights. The improved version of ACO method depends on both factors by the same weight. Thus, this enhancement reduces the blindness of MUs.

VI. CONCLUSION

In this paper, the NRADP prediction technique is proposed to improve the prediction rate for a cellular communications network. This technique depends on the improved ant colony method where two types of visibility were defined: local and global. In addition, the weighting of pheromone and visibility are balanced to enhance the prediction rate by avoiding bias in selecting these factors. On the other hand, the prediction process in NRADP is limited by two thresholds, min and max, which avoid the search stagnation as much as possible while the search stagnation is still unhandled in MPAS. Furthermore, NRADP works on the routing area level rather than the cell level. Thus, it decreases the number of displacements and decreases message passing and the consumption of resources. It also works on core network. The proposed technique still needs some exploration and the time complexity for both techniques should be analysed and compared.

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