An Enhanced Ant Colony Optimization for Routing Area Mobility Prediction over Cellular Communications Network

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Keywords: Ant Colony Optimization, LBSs, Mobility Prediction, Cellular Network, UMTS.

Abstract: Cellular communication networks have become medium to provide various services. Most of the services provided are based on the users' locations, as in location-based services (LBSs); these services include both common voice services as well as multimedia and integrated data services. Used techniques mostly suffered from complex computation, accuracy rate regression and insufficient accuracy. Nevertheless, in the cell side, reducing the complexity cost and preventing the prediction algorithm to perform in two closer time slot. That's why using routing area should be able to avoid the cell side problems. This paper discusses An Enhanced Ant Colony Optimization for Routing Area Mobility Prediction over Cellular Communications Network (EACORA) which is based on developed ant colony Optimization.

1 INTRODUCTION

Mobile networks have become the platform that provides leading-edge Internet services, for instance a person can solve problems in any place without any need to go to his 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 Third-Generation Partnership Project (3GPP), as next-generation in the telecommunications networks.

However, these networks are facing problems such as fragile wireless link, consume resource, denied of services and mobility of mobile users. The mobility location is changing during the constantly movement of mobile user's. The cellular communications network is divided into cells, each cell covers a specific area within the network. The cell contains Base Station (BS) that response to do communications with mobile users reside in the cell. Several cells are grouped together belong to Routing Area (RA). Consequently, the network consists a set of RA. Mobile user being at the boundary of either cell or RA and going to different one, the hand-off occurs and the connection in some cases will be lost because there are no resources to handle the mobile user at new serving area. In contrast, if the resources are enough at the new serving area often the connection lose because the time when mobile user send a request message for re-located and be in the new area is not enough to finish the hand-off procedure, specially that happen at RA re-located. Finally, if the connection does not lose during the Hand-off, a service does not deliver on the time to mobile users.

If the network has enough information about mobile user and neighboured, appropriate artificial intelligent systems are employed. These help the network to predict the next displacement for mobile user with high accuracy, then sensible resource will be saved, delay time for delivering the services will decrease and improve the network functionality such as paging, location update and Hand-off.

The EACORA is proposed in this paper to improve the mobility prediction for Location-Based Services, mobile user's displacement is achieved by the developed ant colony. EACORA 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 that al-

Sh. Daoud M., Ayesh A., Al-Fayoumi M. and Hopgood A..
An Enhanced Ant Colony Optimization for Routing Area Mobility Prediction over Cellular Communications Network.
DOI: 10.5220/0004201004190424
In *Proceedings of the 5th International Conference on Agents and Artificial Intelligence* (ICAART-2013), pages 419-424
ISBN: 978-989-8565-39-6

lows intelligent LBSs disclosing and hence minimizes the computation cost, consumption of resources, reduce the message passing and the overall cost of the location management process such as location update. EACORA scheme utilizes geometrical and topological techniques allowing users to receive desired services timely fashion.

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

2 PREVIOUS WORKS

Locating users as they move from one place to another in a mobile computing environment is the key to providing continuous services with unrestricted mobility. Therefore, the data management in this environment is especially challenging for the need to process information on the move, to cope with resource limitations, and to deal with heterogeneity. One of the applications of mobile data management is LBSs which have been identified as one of the most promising areas of research and development (Barbar, 1999).

In the cell technique (Das and Sen, 1999; J. Biesterfeld and Jobmann, 1997; Kubach, 2000; Kumar and Venkataram, 2002; Shah and Nahrstedt, 2002; U and Rothermel, 2000) a service area is partitioned into several cells. The cell covering the mobile user will page his or her device to establish a radio link in order to track changes in the location of mobile users.

The cells broadcast their identities and the mobile user periodically listens to 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 mobile user sends a location update message to the network (Holma and Toskala, 2001).

Prediction techniques based on a cell technique can be enhanced by heuristic methods and neural networks (Lu, 2003; Capka and Boutaba, 2004). Liou and Lu (Lu, 2003) 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 mobile user is in a cell's edge area, the information is passed to a neural network which predicts from the neighbouring cells the next cell to be visited. Another technique captures some of the mobile user 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 to be visited (Capka and Boutaba, 2004).

The first Ant Colony Optimization (ACO) algorithm, called Ant System (AS)(Dorigo, 1996; Dorigoa and Gambardella, 1997; Dorigo et al., 2000; Dorigo and Di Caro, 1999), Dorigo et al., in (Dorigo, 1996) proposed that to solve the Traveling Salesman Problem (TSP). They proposed a new model to combinative stochastic optimization, based on the ants' behavior, it is inspired from (S.Goss, 1990; Deneubourg and Goss, 1989; Deneubourg et al., 1983). This model is useful when use in greedy heuristic to find acceptable results at the early processing, complex system which need to use the distributed computational to deal with the random space variable, that mean avoiding premature convergence.

The mobility prediction technique in (Daoui et al., 2008) uses the first version of ACO, which the cell dividing has not used, stagnation of search is addressed, and consuming computation cost because there was no limitation for pheromone and the authors did not use the modifications of ACO avoided.

Recent research 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 (Dorigo, 1996) 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, there are no new paths will be found anymore.

Map matching algorithm has been used for mobility prediction. Ren and Karimi developed the map matching algorithm through using other techniques such as Markov chain, hidden Markov fuzzy logic to improve the mobility prediction for wheelchair. In (Ren and Karimi, 2009a), the map matching algorithm has been developed through its dependence on the Markov chain and GPS sensor. The distance and the direction between points which are recorded by GPS are used. Prediction of the direction of wheelchair users in sidewalk is considered as the outcome from (Ren and Karimi, 2009a; Ren and Karimi, 2009b; Ren and Karimi, 2011).

The map matching techniques area proposed in (Ren and Karimi, 2011; Ren and Karimi, 2009b; Ren and Karimi, 2009a) suffered from many major drawbacks. All of them are tested and evaluated for wheelchair only in university camps sidewalk and it works in outdoor only. These techniques are based on GPS navigators. Therefore, anyone who needs to use them must have GPS sensors. However, the GPS sensors lead to extra physical cost bearing in mind that they may not be applicable for all mobile devices.

Moreover, GPS suffers from inaccurate data in narrow roads, high building and is believed to use higher-end GPS relievers to improve the signal, instead of low-end.

A new Splitting-based Displacement Prediction Approach for Location-Based Services (SDPA) (Daoud et al., 2011) has been developed to improve prediction rate, minimizes consumption of resources, and the overall cost of the location management process comparing with PLM. Also, the SDPA reduces the service area and the number of predicted routes during the mobile user trip, by dividing the cell into eight equivalent regions. Thus, the SDPA approach improved the location prediction probability over PLM. The average complexity requirements for usage space are smaller than for the PLM approach. In addition, these techniques still work on cell level which the cost of messages passing and executions time are highly, because the SDPA and PLM executed in tightly time slot.

3 EACORA TECHNIQUE

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

3.1 EACORA Principles

The EACORA based on the responsibility to the RA component instead of using the mobile user or cell. This avoids the computation power required at mobile users, which could be prettier, since power and resource limitations are obstacles for mobile manufactures.

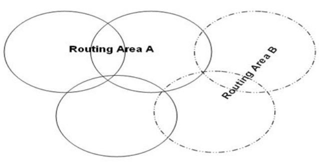

Figure 1: Routing Area Coverage.

The SGSN is managing the RA, each RA contains one or more cells based on the radio specifications and geographical features, as shown in figure 1.

The SGSN is responsible for managing and updating the history displacements for all mobile users which are residing in. Moreover, it handles the prediction model to predict the next displacement for the mobile user according to the current location, history displacements and visibility to surround neighbors.

When a mobile user enters network, the SGSN uses his and neighbors' histories to make a relation between them. Thus, improving the prediction percentage and handling any unusual movement. In contrast, if SGSN does not contain the history displacements for the mobile user, it should use the history of his neighbors.

Each RA is modeled by an ant colony and each mobile user is modelled by an ant. An ant goes from current RA to neighboring RA looking for food. In the food searching, the ant prefers to go through the usual paths or according to the displacement of his neighbors.

3.2 EACORA Prediction

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

At the first entrance of mobile users to the network, no pheromone would be found from any neighbour, that's why the movement goes randomly.

Over the time, each RA has its pheromone which guides mobile users to the most preferable RA for the future displacement.

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

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

Where $P_{C_{RAi,j}}$ the probability that the mobile user at RA i at time t to RA j , t is the time factor, τ the pheromone level and V_{all} is the visibility -memorization- of the mobile user. The visibility here, V_{all}, is obtained from the combination between local and global visibility, accodring to euqation 2.

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

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

Memorization entity is used to calculate the visibility variable *(V)*, it is represented by a vector *(n)* and its length based on the number of adjacent RAs A_{RA}. An element of this vector either local or global represents the ant visibility of an adjacent RA. In a sense, the local memorization reflects the mobile user's behaviour. Where, global memorization reveals all mobile users' behaviours at such RA. The local visibility is managed by equation 3.

$$V_L = \begin{cases} X+1 & \text{if the mobile user exists in } Nr; \\ X=1 & \text{if mobile user does not exist in } Nr; \end{cases} \quad (3)$$

Where V_L is a local visibility, L between 1 and A_{RA}, X is a value starts from 1 and Nr is a local memorization table which stores the adjacent RAs. Meanwhile, the global visibility is represented by equation 4

$$V_G = \begin{cases} Y+1 & \text{if the mobile user exists in } Mr\ ; \\ Y=1 & \text{if mobile user does not exist in } Mr; \end{cases} \quad (4)$$

V_G is a global visibility, G between 1 and A_{RA} for each mobile user, Y start from 1, Mr is a global memorization table which stores the adjacent RA, where each mobile affects on this equation.

When a hard hand-off occurs for a mobile user, the mobile user changes the RA to another one. At this time, the mobile user deposits his pheromone on the RA which has been just left. The amount of pheromones is deposited on each RA represented by equation 5.

$$\Delta\tau_{i,j} = \begin{cases} \lambda * Q * \tau_{staying\_in} & \text{if } \lambda * Q * \tau_{staying\_in} < Q \\ Q & \text{if } \lambda * Q * \tau_{staying\_in} >= Q \end{cases} \quad (5)$$

Where $\Delta\,\tau_{i,j}$ is the pheromone quantity that would be laid down on the RA by the mobile user when he 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 mobile user 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 exceed the Q value since this amount proportional increases over time.

When the value of $\Delta\,\tau_{i,j}$ is less than Q, the mobile user's pheromone affects the pheromones that held by RA in a proportional to the time spent in that RA. If $\Delta\,\tau_{i,j}$ greater than or equal to Q, the mobile user is spending very long time in the RA, that means the mobile user is working or living there, this leads to have pheromone quantity greater than Q, therefore the quantity will lay down is all Q, to avoid the bias of the quantity that may laid down and stagnation of search.

In EACORA after δT the evaporation process will take a place to decrease the pheromone level at each RA in the network, this is represented by equation 6.

$$\tau_{acc\_RA_i}(t+1) = \tau_{acc\_RA_i}(t) * (1-\rho) \quad (6)$$

Where $\tau_{acc\_RA_i}(t)$ represents the accumulative pheromones in RA i, $(1-\rho)$ is the evaporation rate.

A small value of ρ carrying out to pheromone evaporation slowly and the pheromone will accumulate more on a RA. A large value of ρ leads to forget the behaviour of other mobile users and the prediction turns into random way. In a case when ρ is equal 1 the prediction becomes completely random. The value of ρ affects on the prediction rate by permitting to forget the behaviour of the elder mobile users and to remove the bias mobile users' behaviour.

Probabilities of all RAs that surround the RA where the mobile user resides in are calculated in equation 1, the highest probability would be taking in consideration as next RA that mobile user will visit. Hence, the next displacement is expressed in equation 7.

$$Next_{RA} = \max(P_{C_{RAi,j}}(t)) \quad (7)$$

Where $Next_{RA}$ is the next displacement.

4 DISCUSSION OF SIMULATION AND RESULTS ANALYSIS

4.1 Parameter Setup and Environment

A simulator was created using Java programming language for the EACORA, in which the algorithm based on The developed ant colony model is implemented and tested. Each experiment consisted of 10 different iterations to improve accuracy. Each experiment took five hours, as shown in table 1.

Table 1: 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

4.2 Experiments and Result Analysis

The experiments in this section made to obtain the optimal value for each parameter; the parameters were tested to evaluate the RA mobility prediction technique, which include: Parameter-1:the factor which affects on evaporation rate. Parameter-2: quantity of the initial pheromone that would be laid on each RA. Parameter-3: calculating the participation ratio of local visibility compared with global visibility. Parameters-4: determining the effectiveness ratio between pheromone and visibility, which represented by α and β.

For parameter 1, the prediction rate is tested over varied evaporation rates. Figure 2 shows the prediction rate percentage over the change on factor ρ. The experiments were carried out on a range of ρ between [0, 1], where its increment was moved up by 0.1. From the experiments depict the optimal values of ρ were between 0.6 and 0.8 where the highest prediction rates were achieved over the change on ρ. These values encouraged the RA developed mobility prediction technique to avoid search stagnation, finding new solutions and prevent the deletion of any new solution.

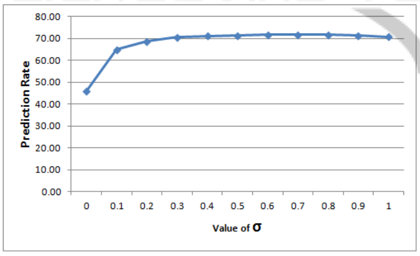

Figure 2: Prediction rate according to the different values of ρ.

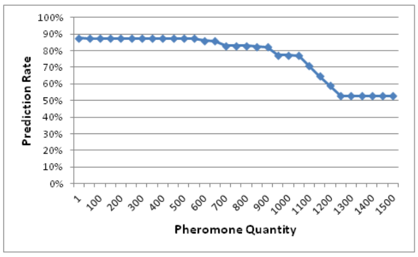

Figure 3: Prediction rate over varied initial pheromone quantities.

For parameter 2, the prediction rate over varied initial pheromone quantities is examined. Figure 3 describes the initial pheromone quantity that would be laid down on each RA before starting the running of the technique. The prediction rates between 88 and 53 over varied amounts of pheromone quantity. The highest prediction rate was 88 when the amounts of pheromone setup to 1, as a result the best amount of pheromone to be laid down was 1 unit. The use of small amount of initial pheromone would save computation cost. For showing the effectiveness of pheromone quantity that will lay down during the running of the algorithm the next parameter is addressed.

For parameter 3, the significant combination of local and global visibility for the mobile user is validated. Figure 4 shows the prediction rate according to the changing between local and global visibility participations. Based on equation 2 two values should be avoided in order to utilise these two concepts, these values are 0 and 1.

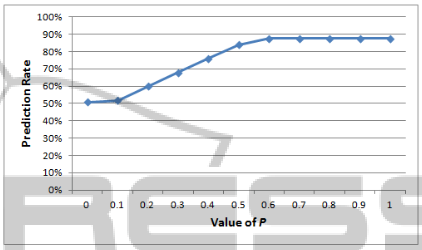

Figure 4: Prediction rate according to the changing values of P.

When the value of P equals to zero, the local visibility would be eliminated that means the RA will use the neighbours' heuristic information to predict the next displacement for a mobile user. Thus the mobile user cannot visit any of its favourites RA. In other words, the mobile user displacements would be predicted randomly.

To achieve balancing between local and global visibility, P was set to 0.6. This value guarantee a full participation of both local and global visibility, as well as better prediction rate would be obtained, see figure 4.

For parameter 4, the prediction rate is tested over varied distance between alpha and beta. Figure 5 shows the effect that resulted from varying the values of alpha and beta in order to determine the best values to gain the highest prediction rate. As shown in figure 5, it was noticed that when both Alpha and Beta were equalled the prediction rate was highest. Therefore, both Alpha and Beta are going to be chosen according to the results, meaning that the values of Alpha should be chosen to be equal to values of Beta to achieve better prediction rates.

5 CONCLUSIONS AND FUTURE WORK

This paper introduced new routing area displacement prediction technique for location based services. This technique is based on developed ant colony Optimiza-

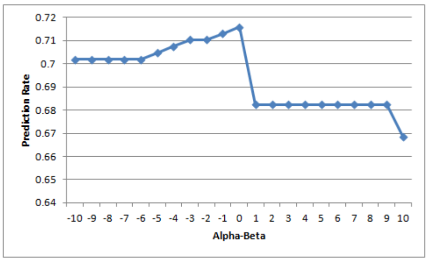

Figure 5: Prediction rate according to the varied Alpha-Beta.

tion which achieved a high prediction rate up to 88%. In addition, this paper has obtained the optimal values for all the parameters that improve the prediction rate and reduce the complexity. More work needs to be carried out, for example the different number of mobile users effect on using the new technique have to be tested. In addition, the effect of the mobile users' history, complexity time and memory usage with the current techniques.

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