IJISET - International Journal of Innovative Science, Engineering & Technology, Vol. 2 Issue 7, July 2015.
www.ijiset.com
ISSN 2348 – 7968

Use of Hidden Markov Mobility Model for Location Prediction and Biclustering for Cache Replacement in MANET

Bhakti D. Shelar[1], Mr. D. K. Chitre[2]

[1]Department of Computer Engineering,
Terna Engineering College, Nerul,
Mumbai University, Navi Mumbai, India.
shelar.bhakti@gmail.com

[2]Department of Computer Engineering,
Terna Engineering College, Nerul,
Mumbai University, Navi Mumbai, India.

Abstract

Now a days students, office staff and even study scholars are using portable appliances such as laptops, mobile phones and PDAs. These devices are mostly wireless, hence they can be carried along with us. So, such mobile devices are fetching much popularity by the users. Also, They are available in affordable prizes. Previously cell phones were used only for incoming and outgoing calls. As the days are passing, cell phones are becoming smarter. They are able to provide value added services such as E-banking, online purchasing, Location based services(LBS), etc. In LBS, cache memory play an important role to hold user's location dependent data. So, in proposed system we developed a cache replacement policy for maximum utilization of limited cache memory. We used Hidden Markov Model for predicting the user's most probable

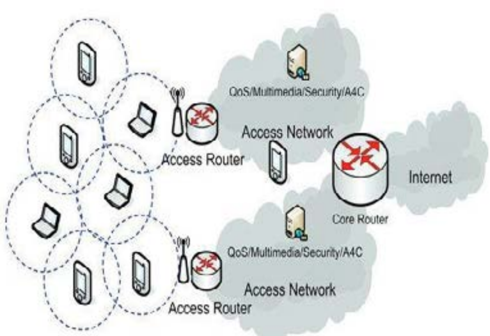

Fig. 1: Wireless devices forming the Adhoc Network[16]

future location . Also for Bi-clustering, we defined one cluster of locations and one cluster of data. This strategy is considered as Bi-clustering approach. We compared proposed cache replacement policy with Least Recently Used (LRU), Furthest Away Replacement (FAR) and Policy using only Hidden Markov Mobility Model. Results prove that proposed policy does the more accurate cache replacement and gives cache hit ratio around 0.45.

Keywords: *Cache Replacement Policy, Hidden Markov Model, Bi-clustering, Location Based Services, Trajectory*.

1. Introduction

In Mobile Adhoc Network (MANET), wireless infrastructure exists. All the devices form a temporary-basis network for information exchange. Every device is freely moving across the area. Direction of movement of user is fixed or varying. When an user gets any data packets, it checks destination address. If this address is not belonging to user's address, the user forwards this data traffic across the network. It uses the wireless path. Important feature of MANET is each device is efficient enough to store the data required for the proper route traffic.

As shown in Fig. 1, integration of MANETs are shown with various networks such as external Internet. These types of networks are capable to be operated by themselves by using mutual communication protocols. Otherwise, they are inter connected to the Internet through Access Router. By using cryptography strategies, security for data traffic is achieved. Wireless devices may contain one or multiple and different transceivers between nodes.

Location Dependent Information Services (LDIS) i.e. LBS are applications for smart phones. These applications require information related to the user's movements and also about locations he visited. These services work on query-reply approach and provide useful information to the user such as "nearest ATM " or "nearest Hospital". Also they can provide push-based option which periodically provides location relevant and useful information to the user.

As shown in Fig. 2, wireless devices form cellular network which is connected through satellites. One location server is maintained to store data local to that cellular network, which is provided to the client.

The frequently accessed data is then stored in clients cache memory. An LBS needs the five basic components, they are end user's mobile device, a positioning component like Global Positioning System(GPS), a content provider to supply the end user with geo-specific information, the service provider's software application, a mobile network to transmit data and requests for service.

Fig. 2 : Location Based Service System [17]

Now, cache mechanism in MANET possesses some limitations, like limited cache space, limited battery backup and mobile nature in greater extent. If the data is available in local cache itself, then user gets faster reply. In other words, transmission delay is reduced to effective extent and less battery power is consumed. An efficient cache replacement strategy becomes useful for differentiating between the data items to be kept in cache and that is to be removed when cache is not empty. Instead of selecting any data item from cache, system performance will be better if we select data item that is not frequently asked or not relevant to the users current location. So an effective replacement strategy is essential to achieve high cache hit ratio.

The rest of the paper is organized as follows. Section 2 briefly describes survey of the various cache replacement policies. Section 3 gives conceptual description about proposed methodology. Section 4 and 5 describes Experimental Evaluation and Result Analysis respectively. Section 6 concludes the paper.

2. Literature Survey

Existing cache replacement policies(CRP) can normally be divided into three categories, they are 1) Temporal Based CRP 2) Direction and Distance Based CRP 3) Prediction Based CRP. The temporal based strategy works on the timestamp of the data accessed from the database. So a data item can be requested for few number of times or a large number of times. So number of access of a particular data decides the recency and frequency of it. This parameter determines that whether that data should be maintained in database or evicted. But these policies give satisfactory performance for stable user and prove inefficient for mobile user which free to change his direction.

Direction and Distance Based CRPs think for the mobile nature of user. So, while making decision about which data should be replaced and which data should be maintained, these policies consider moving direction. Also they give importance to distance between location of data and current location of user.

Prediction Based CRPs analyze the history of users' movements. They try to find some pattern existing in users movements. Based on these observations and analysis, they predict the user's probable future location. They remove the data which is not related to this predicted location and place only that data which shows relevance with this location. Several studies and proposals are depicted for above three approaches.

Least Recently Used (LRU), Least Frequently Used (LFU) and LRU-k [9] are the temporal based replacement policies. They maintain recently used or frequently used data in the cache memory. In MANET environment, clients access pattern don't exhibit only temporal locality, but also exhibit dependence on location of data, location of the client and direction of the clients movements. So, these policies are unsuitable for supporting location based services as they do not consider the movement of mobile clients and location of data items. Hence, depending only on temporal locality when making cache replacement decisions will result in poor cache hit ratio in LBS.

To Solve these difficulties , some location-aware cache replacement strategies have been proposed for location based services. Manhattan Distance-based cache replacement policy [7] supports location dependent queries in urban environments. Cache replacement decisions are made on the basis of distance between a clients current location and the location of each cached data object. Objects with the highest Manhattan distance from the clients current location are evicted at cache replacement. Furthest Away Replacement (FAR) [9] policy uses the current location and movement direction of mobile clients to make cache replacement decisions. Cached objects are grouped into two sets, viz., in-direction set and the out-direction set. Data objects in the out-direction set are always evicted first before those in the in-direction set.

In Probability Area Inverse Distance (PAID) [15] policy, the cost function of data item *i* considers access probabilities (Pi) of data objects, area of its valid scopes A(*vs*i) and the distance D(*vs*i) between the clients current position and the valid scope of the object concerned. This distance is called as data distance. None of these cache replacement policies are suitable if client changes its direction of movement quite often. Existing cache replacement policies only consider the data distance but not the distance based on the predicted region or area where the mobile user may be in future. Very few of these policies account for the location and movement of mobile clients.

In this paper, we study the problem of analyzing human location histories to predict the next places to be visited This we have done by using an approach based on Hidden Markov Models. This paper proposes an approach to train the HMM by using Baum-Welch algorithm and then to predict the future locations of mobile users. keep location-related data in the cache and evict unrelated data from the cache. These decisions are made on the basis of users previous visits to other locations, and leveraging on Hidden Markov Models for capturing the patterns included in previously collected location histories. Then with the help of two clusters viz. data cluster and location cluster, we fetch the data from the category expected from users. This approach is known as Bi-clustering.

3. Proposed Methodology

3.1 Hidden Markov Model

The diagram in Figure 3[1] shows the general architecture of an instantiated HMM. Each shape in the diagram represents a random variable that can adopt any of a number of values. The random variable x(t) is the hidden state at time t. x(t) € {x1, x2, x3} random variable y(t) is the location visited at time t (with y(t) € {y1, y2, y3, y4}). The arrows in the diagram denote conditional dependencies. Conditional probability distribution of the hidden variable x(t) at time t, depends only on the value of the hidden variable x(t -1), and thus the values at time t-2 and before have no influence. [1]This is called the Markov property. The value of the observed location y(t) only depends on the value of the hidden variable x(t), at time t.

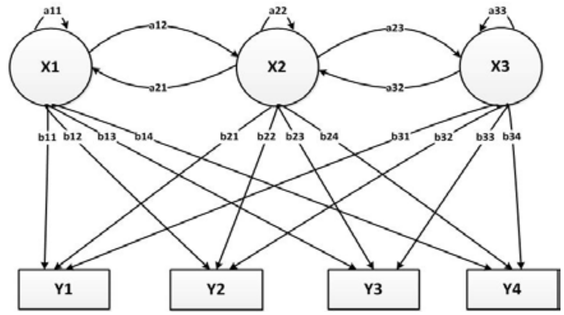

Fig. 3 Hidden Markov Model[1]

We have to calculate probabilities for a given observation sequence. The probabilities of observing particular sequence in the form, Y=< y(1), y(2), y(3),…, y(L)> of length L is given by

$$P(Y)=\Sigma\ P(Y \mid X)P(X)$$

Where, X is hidden variable, i.e. previous location of user and X= <x(1),x(2),x(3),…..>. Y is current location of user, visited at time t and Y is given as Y= <y(1),y(2),y(3),…..>. Training of HMM means output sequence X is given, we have to find best set of state transition and output probabilities. For this we use Baum-Welch algorithm. For this algorithm, HMM is described as **λ=(A, B, π).** Where, A is transition matrix between states. B is matrix of output probabilities in a given state and. π is initial state distribution. Now, given input is Y=< y(1), y(2), y(3),…, y(L)>. Baum-Welch finds out the **λ* =**max λ P(Y| λ). So here parameters for λ are found and λ is optimized. This process repeats till a number of particular steps reached. Two steps are used to tackle this problem, they are forward and backward step.
In forward step $\alpha_i(t+1)=b_i\ (ot+1) \sum_{j=1}^{N} \alpha(t) \times a$ where, N is set of possible state, a is transition probability and bi is emission probability. In backward step, we use formula

$$\beta i(t)=\sum_{j=1}^{N} \beta(t+1) ai,j\ bj\ (o+1)$$

In this way, parameters for HMM are estimated. Now, given the sequence, Y=< y(1), y(2), y(3),…, y(L)>,y(L_{next})>. This is a sequence of visits. Finally HMM predicts the L_{next} which is possible location to be visited next.

3.2 Concept of Biclustering

In MANET, all users are mostly moving. It means their location is not fixed. So it becomes helpful to keep the resources in the grouped manner. Also user's positional information also can be managed group-wise. This concept is well-known as clustering. Here, we have used

Bi clustering mechanism which evaluates cluster of data and cluster of locations. Total 40 locations we have used in our simulation. All are numbered from 1 to 40. In data cluster three categories are derived. One stores ATMs, second one is for Hotels and third one is for Hospitals. This information is gathered from [18]. The data information is stored in a notepad file and then this file is loaded in our matlab code.

4. Experiment Evaluation

Primary performance metric is cache hit ratio. Cache hit ratio is defined as ratio of number of queries answered by client's cache to the total number of queries generated by client. Higher the cache hit ratio, higher is the local data availability. We implemented the proposed approach for pedestrian movement prediction through an existing implementation of the algorithms associated with Hidden Markov Models (i.e., the Baum-Welch and the forward-backward procedures), latter validating the proposed ideas through experiments with the GeoLife dataset, i.e. a GPS trajectory dataset collected in the context of the GeoLife project from Microsoft Research Asia, by 178 users in a period of over three years from April 2007 to Oct. 2011. In the GeoLife dataset, a GPS trajectory is represented by a sequence of time-stamped points, each of which containing latitude and longitude co-ordinates. The full dataset contains 17,621 trajectories with a total distance of about 1.2 million kilometers and a total duration of 48,000+ hours. The trajectories were recorded [12][13][14].

For experimental evaluation, we considered one temporal based LRU CRP, one distance based CRP i.e. FAR and one prediction based CRP i.e. only HMM based CRP. we took cache size 4,6,8,10,12,14,16,18 and 20 bytes. For these size, we computed cache hit ratio for all four CRPs.

5. Result Analysis

Table I Cache Hit Ratio calculated for varying cache size

Cache size in bytes	LRU	FAR	HMM	HMM+ BC
4	0.154	0.259	0.356	0.446
6	0.156	0.260	0.357	0.447
8	0.157	0.267	0.361	0.447
10	0.161	0.252	0.357	0.445
12	0.157	0.253	0.361	0.446
14	0.167	0.251	0.359	0.446
16	0.168	0.258	0.361	0.449
18	0.170	0.257	0.371	0.448
20	0.168	0.256	0.375	0.449

As shown in Table I, LRU gives cache hit ratio(CHR) around 0..14, FAR gives CHR around 0.25, HMM based CRP gives CHR around 0.35 and our proposed HMM with Bi clustering CRP yields CHR of 0.45, which is highest. When cache hit ratio improves, it indicates that cache memory's utilization is maximum. So reply for user's query is provided from client's cache memory only. Observations are plotted in 2D X-Y coordinate plane in figure 4.

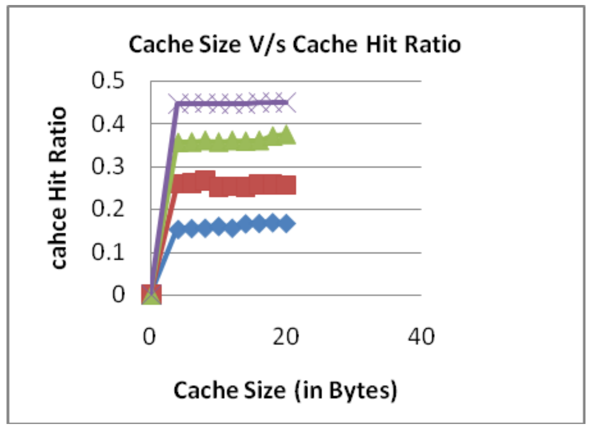

Fig.4. Comparison of performances of LRU, FAR, HMM and HMM with Biclustering.

In figure 4, on x axis, cache size in bytes is plotted and on y axis corresponding cache hit ratio is plotted. The purple graph-line indicates performance of proposed CRP using HMM with Bi clustering, green line indicates performance of HMM based CRP, red line indicates performance of FAR and blue line shows performance of LRU.

6. Conclusion

HMM based Cache Replacement Policy takes into account the location user currently resides in. So, the prediction accuracy increases. Also it considers the user's moving direction and traces location histories of client. Then it utilizes these data for prediction of most probable future location. Bi-clustering helps to give data which is most interested by the user. Also due to Bi-clustering, data specific to a location and to a type (i.e. a Restaurant, a Hospital or an ATM) is stored into cache. So, in turn it makes maximum utilization of the cache. So, HMM based

CRP along with Bi-clustering, proves most accurate replacement compared to the LRU and FAR. LRU considers only no. of times data item is accessed. This information is partial and abstractive in order to make replacement decisions. FAR considers current location and movement direction of client to take replacement decisions. FAR neglects temporal properties of data item leading to less accuracy.

The cache hit ratio is stable though we vary size of cache. For future work, we would also like to experiment the Mixed Markov Model and extension of Conditional Random Fields(CRFs) which can be used in association with Bi Clustering. This is kept for future. Also HMM can also be corporated with Conditional Random Fields(CRFs). This model deals with pattern recognition of the frequently used data. This is a state-space model which attempts to capture variations in spatial sequence.

Acknoweldgement

The authors feel very happy to present their gratitude towards Terna Engineering College, Nerul, Navi Mumbai, for technical support offered required for experimental evaluation. Also they are thankful to Dilkap Research Institute of Engineering and Management Studies, Neral, for continuous guidance and inspirations.

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Bhakti D. Shelar received the B.E.(Computer) degree from Terna Engineering College, Nerul , Navi Mumbai. Worked in S. S. Jondhle College of engineering and now working in Dilkap Engineering College, Nerul. Pursuing M.E.(computer) from Mumbai University.