An Effective Prefetching Technique for Location-Based Services with PPM

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Abstract

Location-Based Services (LBS) are available on hand-held devices and become a field of active research since the recent advances in wireless communication and mobile environment. Due to the constraints of bandwidth of network, space of storage and energy of battery in the mobile client, slow information transformation between client and server declines the quality of LBS. The techniques of caching and prefetching information is usually adapted to increase the performance of information transformation. However, almost of current techniques of caching and prefetching uses the static metrics to guide the operations of the techniques. In this paper, we adapt the technique of Predication by Partial Match (PPM) to capture the dynamic behavior of drivers applied to the service route guidance. An experiment was conducted to compare the performance of our approach and that of with fixed probabilities. It is observed that PPM had a better effect in capturing the popular phenomena then the fixed probabilities.

Keywords: Caching, location-based services, prefetching, mobility model, wireless network.

1. Introduction

The advances in wireless communication and mobile context awareness are increasingly making the Location-Based Services (LBS) are available on hand-held devices and become a field of active research [1, 12]. A LBS is a service for mobile users with the suitable terminals where the awareness of the current, past or future location is integrated to the service. Users' mobility recognized by network would be an important clue to provide the qualified LBS.

LBS has introduced in various application scenarios, such as location identification, emergency support, transportation management, and route guidance, etc [9, 14, 16, 17]. Location identification is used to guide a user lost his path on the way with the current location environment. Emergency support, in a catastrophic situation, requires some rescue operations which could be coordinated with respected to actions, location, and time. Transportation management applies to the logistics of transport systems, such as the arrangement in case of smart factory applications with many distributed partners. Route guidance are used to provide the related information of a route selected by a user.

Caching and prefetching has been adapted to increase the performance of information transformation in mobile environment for prompting the quality of LBS. In general, caching and prefetching techniques are good for static information accessing situations [5, 6, 11]. In this paper, route guidance is used to study our approach since it is almost based on static information. However, almost of caching and prefetching techniques for navigation behavior used probability or metrics defined by some static attributes. We observed that navigation behavior derived by customers(drivers) should be dynamic. Thus, we will use PPM to model the dynamic behavior of drivers for increasing the performance of caching and prefetching route information [4, 8, 13].

Persone study of caching and prefetching is a representative result in the field [10]. Our motivation is the fixed probabilities should be dynamically managed in order to reflect the history sensitive of a route in the service of route guidance. So, in our approach, we study the effectiveness of modeling dynamically the more effective mobility model from accumulating the history of a route by PPM. Therefore, the results of our study is compared with some results in [10].

The remainder of the paper is organized as follows: We first discuss related work on mobile system model, which has provided a foundation and motivation for our research. We then delineate the processes of applying PPM to enhance the operations of prefetching. Then, an experiment is shown to compare the performance of our approach and that of with fixed probabilities. Finally, we review the current work of our approach and suggest ex-

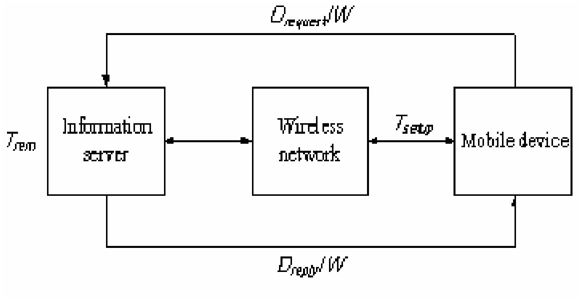

Figure 1: A system model of mobile environment.

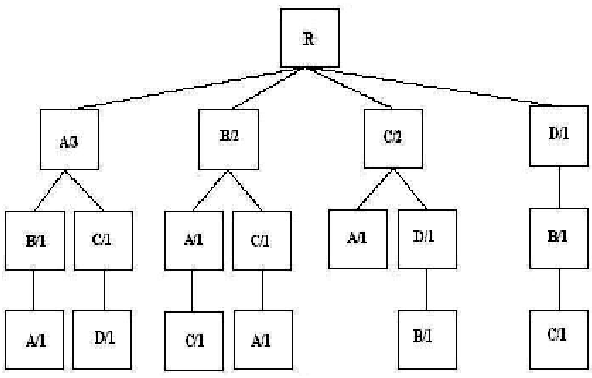

Figure 2: A Markov prediction tree of sequence $< ABACDBCA >$.

tensions that might be valuable.

2. System model and performance measurement

In general, the system model for providing LBS is depicted as Fig 1, consists of three components: mobile devices, wireless network, and information server. Users get the request information from the information server via wireless network with users' mobile devices. For a LBS, the information server could manage the information related to a location. So, the mobile device can request the information server to send location-related information to the user with user's position [1].

When a user enters a new zone in the covered area of the information server, his mobile device should capture new information of the new zone from the server. However, if the information is already existed in the mobile device, it is not necessary to capture the information from the server. So, the average latency to get up to date information when the user enters a new zone is given by $L = T_{det} + T_{load}$, where T_{det} is the average time needed to detect the zone change, while T_{load} is the average time needed to retrieve and start making available the information to the user. T_{det} strongly depends on the technique used to detect a zone change. Hence, we will not consider in the following the contribution of T_{det} to the latency, and focus our attention on T_{load} [10].

And, the following measurement followed the descriptions of Persone in [10]. Assuming the availability of a cache in the portable device, T_{load} can be expressed as

$$T_{load} = \frac{T_{rem} \times M + T_{loc}(N - M)}{N}$$

where T_{rem} is the time needed to retrieve and start loading the information from the remote server responsible for the information service, and T_{loc} is the time to retrieve and start loading information that is stored in a local cache of the user device (with $T_{loc} \ll T_{rem}$). M is the average number of cache misses, N is the average number of visited zones.

Referring to Fig 1, $T(n)$ is the average active time at the nth connection with the remote server.

$$\begin{aligned} T(n) &= T_{setup}(n) + D_{request}(n)/W + T_{rem} \\ &\quad + D_{reply}(n)/W \end{aligned}$$

where T_{setup} is the average setup time to connect to the remote server, $D_{request}(n)$ is the size of the request sent to the server, $D_{reply}(n)$ is the size of the loaded information, and W is the bandwidth.

Then, the energy consumption modeled by the overall average active time of the mobile environment can be expressed as follows:

$$T_{tot} = \sum_{n=1}^{m} T(n).$$

PPM is a commonly used technique in Web prefetching where prefetching decision are made base on historical data/behavior [15]. The information extracted from historical data are dynamically maintained with a Markov prediction tree. For example, a sequence of zones in a route $S =< ABACDBCA >$ could be modeled by a Markov prediction tree with order 2 shown as Fig. 2.

Now, the prefetching task can be assisted with the knowledge contained in the Markov prediction tree, explained as follows. When a mobile client requests the service, the information server will maintain the PPM model coordinated with location server. Then, the prefetching data set is built by the information server based on the current PPM model. And, the data in the set will be transferred to the mobile client via wireless network [9].

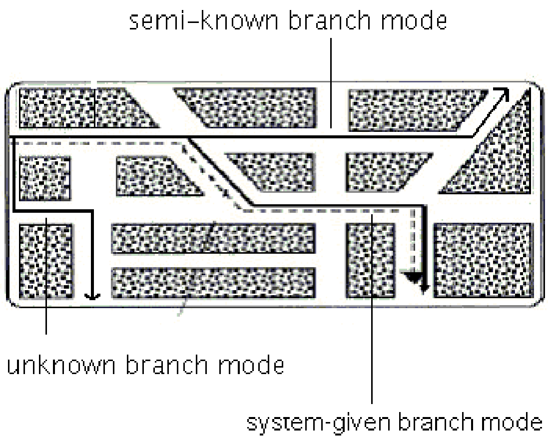

Figure 3: Mobility modes in the experiment.

3. Experiments

An experiment of building our approach with Java is conducted. Moreover, for comparing with the result in [10], we set the same parameters values, as follows: $T_{loc} = 10$ ms, $T_{rem} = 5$s, $req(n) = 200$ bytes, $W = 25$ kbytes/s, $T_{setup}(n) = 30$ms. And, the data size of a chunk for a zone is $10K$ bytes.

In our approach, for simulating the behavior of users, the mobility model is designed as a three-mode movement: system-given branch mode, semi-known branch mode, and unknown branch mode. In the first mode, users follow the system-given branch mode until user arrival the destination. On the other hand, in the semi-known branch mode, users can leave the route on the middle of the way. And, in the unknown branch, users have random walks on road as soon as the beginning of starting the prefetching service. The diagrams of the three modes are shown in Fig. 3, where dashed and solid lines denote the system-given and user-driven routes, respectively.

For modeling the various mobility model, we set the weights of modes of system-given branch mode, semi-known branch mode, and unknown branch mode. Therefore, 7:2:1 denotes 70%:20%:10% users will be in the three modes, respectively. The probabilities of leaving and going forward from the current zone in [10] are set with the same weights.

The comparison of T_{tot} and T_{load} are shown in Fig. 4 and Fig. 5, where the units of y-axis are seconds. In the initial case 10:0:0, the corresponding PPM tree has not built yet, our approach use the system-given branch mode so that T_{load} is the same as Persone approach. However, since we need time for building the PPM tree, for T_{tot} our approach is slower than Persone approach. After the PPM tree is built, our approach have the better performances in T_{tot} and T_{load} than Persone approach since the dynamic adaption also occurs in the new route.

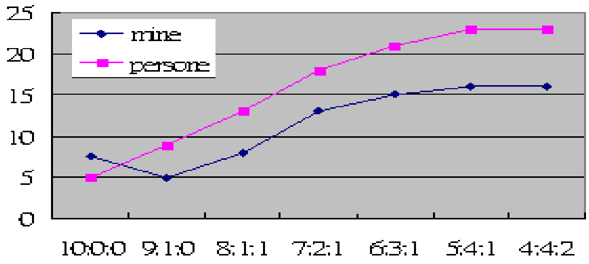

Figure 4: A comparison of the performance T_{tot}.

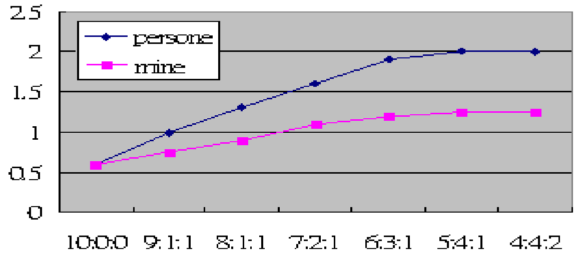

Figure 5: A comparison of the performance T_{load}.

4. Conclusion

We had conducted a study to compare the effectiveness of modeling movement behavior of a route with the historical behavior of many users. We show that mobility modeled with PPM had a better result on the prefetching service than that of a Markov process with the fixed probabilities. However, the pay of keeping the tree of PPM may be expansive for the need of a large amount of storage space [3, 7].

For the extension of the study in the future, we consider using Tries instead of general trees to capture the information PPM such that the performance and storage space of PPM may be improved. On the other hand, popularity-based PPM reduced some nodes in a PPM tree [2]. The relationships between popularity and mobility would be explored to reduce the storage requirement of PPM.

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