Computer Communications 34 (2011) 816–834

Contents lists available at ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

An adaptive location prediction model based on fuzzy control

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ARTICLE INFO

Article history:
Received 14 January 2010
Received in revised form 22 July 2010
Accepted 2 September 2010
Available online 8 September 2010

Keywords:
Mobile computing
Adaptive location prediction
Local linear regression
Fuzzy controller

ABSTRACT

We focus on the proactivity feature of mobile applications. We propose a short-memory adaptive location predictor that realizes mobility prediction in the absence of extensive historical mobility information. Our predictor is based on a local linear regression model, while its adaptation capability is achieved through a fuzzy controller. Such fuzzy controller capitalizes on an appropriate size of historical mobility information in order to minimize the location prediction error and provide fast adaptation to any detected movement change. Our prediction experiments, performed with real GPS data, show the predictability and adaptability of the proposed location predictor.

1. Introduction

One of the more intuitive capabilities of the mobile applications is their *proactivity*. The prediction of the user's mobility behavior enables a new class of location-aware applications to be developed along with the improvement of the existing location-based services [1,2]. Even at the network level, mobility prediction assists in critical operations like handoff management, resource allocation, and quality of service provisioning.

Two classes of location (path) prediction schemes can be found in the current, mobile computing, literature. The first class includes schemes based on extensive historical data of the user movement. Such a scheme can be characterized as stateful. In a stateful scheme the prediction process relies on the *matching* of established (historical) movement patterns with the user movement experienced up to moment of prediction in order to estimate the future location of the user. Pattern-based and data mining approaches as well as machine learning techniques (e.g., learning automata) can be classified in this category. Contrary to the stateful scheme, a stateless model does not take into account extensive historical movement information for the prediction process. Instead, it uses of *a short sliding window* of historical movement information. Such scheme applies statistical techniques (e.g., extrapolation) on the recent movement information (window) in order to predict the future user location. The stateless scheme does not assume regularity in the user movement, as opposed to the stateful scheme, but proceeds with predictions based only on short-term spatiotemporal knowledge. Moreover, the prediction process comes along with adaptation techniques for certain parameters of the statistical techniques to fully cover the potential randomness of the user movement. One could also define hybrid schemes based on the stateful and stateless mechanisms that are invoked and collectively taken into account for joint decisions (e.g., weighted decisions).

In stateful prediction techniques, the user mobility pattern is created using location-time series. The main drawback of stateful techniques is the detection, classification, storage and general handling of the mobility patterns. The size and freshness of the mobility pattern is directly linked to prediction accuracy. Limiting the size of the user's history leads to loss of information, which results in false predictions, and, on the other hand, redundant or excess historical knowledge results to noisy information and biased predictions. Moreover, such methods require a certain type of training (especially off-line learning schemes are applied, e.g., unsupervised clustering) and demonstrate limited tolerance to unknown & unforeseen movement patterns. A detailed discussion on such approaches can be found in [3]. All the reported drawbacks led us to introduce a stateless scheme for movement prediction without considering user movement profiles and pattern-based techniques. The challenge is to introduce an approach based on

- short-term spatiotemporal knowledge on user mobility behavior,
- detection and quick adaptation to changes of the user mobility behavior, and,
- very low requirements on storing and manipulating short-term historical movement data.

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doi:10.1016/j.comcom.2010.09.001

We present an approach for mobility prediction exploiting only the current spatiotemporal knowledge on the user's mobility. Our aim is to address the problem of mobility prediction in the absence of large historical mobility information for the considered user (s). The proposed mobility prediction approach can be applied whenever the mobility behavior of a user is not known a priori. For instance, consider tourists that visit a town or a freshman in a University campus. However, due to the absence of past mobility patterns, mobility prediction has also to regularly adapt to unseen user movements. The proposed scheme can, quite accurately, predict the traveling trajectory. This is achieved by using and dynamically adjusting only local current spatiotemporal knowledge on the user's mobility behavior having very short relevant historical information. The main objective of our approach is to circumvent the difficulties that arise in predicting the user's future location when extensive knowledge on the history of user's traveling patterns is not available or the user behaves quite randomly. Another challenging point is the determination of the capacity of the relevant historical information used for mobility prediction. The capacity of the relevant historical information varies among mobile users since they exhibit different movement behaviors. In addition, more interestingly, the capacity of the relevant historical information is time-varying for a single user itself. This is because the mobile user can abruptly change his/her movement behavior, which has to be reflected in the capacity of the relevant historical information in order for the mobility prediction system to adjust to such unseen, new changes.

Prior work in the area of location prediction includes knowledge storage and process about the user mobility pattern. The model in [4] uses Naïve Bayes classification over the user movement history. Such state-full model assumes that the mobility patterns follow a normal distribution. However, such assumption is not always true since mobility information refers to trajectories of unknown distribution. The (stateful) learning automaton in [5] follows a linear reward–penalty reinforcement learning method for location prediction. This model needs to store all possible transitions of the user's mobility pattern, thus, leading to considerable memory requirements. The stateless model in [6] deals with mobility prediction without prior knowledge of the user's behavior similarly to our approach. It applies evidential reasoning for mobility prediction based on social activities of the mobile user besides location information. Nevertheless, such model involves significant computational complexity (due to the Dempster–Schafer reasoning algorithm) once the amount of possible user locations increases and requires detailed user information (e.g., daily profile, preferences, favorite meeting places). Other methods for predicting user trajectories have also been proposed in the literature but these have generally been limited in scope since they consider rectilinear movement patterns only (e.g., highways) and not unknown patterns [7]. The system in [8] adopts a Markov model to predict the user's future location. This implies also a large history of user movements for mining information from GPS traces. The hybrid model in [9] uses self-organizing feature map and multi-layer perceptron networks for learning all the movement patterns for a set of users in cellular networks. It uses off-line training based on the movement history of a large number of mobile users. This approach also accumulates a large volume of information. We also report prior work in the area of adaptive location prediction, where the predictor tunes its model subject to changes in the user's mobility behavior. Specifically, the authors in [10] introduce a state-full prediction model that adopts Adaptive Resonance Theory (ART) over GPS traces. ART is an online learning and adaptive algorithm capable of detecting changes and adapt/update only parts of the model, thus, providing for the fast adaptation of the underlying model. This approach achieves probability of successful predictions similar to our model. The drawback of this model is that it has significant storage requirements in order to store the user patterns. In addition, the model in [10] responds slowly to changes, thus, cannot achieve fast adaptation to previously unseen mobility behavior.

In this paper, we discuss the design and implementation of an *adaptive*, *short-memory* location predictor (LP). The LP does not require an extensive knowledge base of past user movements. Instead, the LP estimates the future location of the mobile user based on short-term movement information. That is, the LP exploits only local spatiotemporal knowledge of the user movement trying to predict future locations near in time. Evidently, this requires that the LP dynamically adjusts its model for future decisions on location estimations. Since there are no stored historical patterns or other representative knowledge on the user's mobility behavior, the LP has also to be efficient even in the case of random (spontaneous) movement changes, e.g., sudden turns. On the other hand, the LP should reach a stable condition (model) whenever the user does not change his/her mobility behavior for long. Therefore, the LP should be able to rapidly detect changes in mobility behavior and adapt its model to the *current* behavior, thus, providing for fast adaptation of the model.

The criteria that we establish for the performance assessment of the adaptive LP take into account the system requirements (storage capacity) and the computational effort for prediction and fast adaptation. Besides the prediction accuracy, i.e., the precision of location predictions, we are interested in the size/capacity of the information that LP has to process for making predictions. We should stress that in our case, the consumed memory is extremely low if compared with other adaptive techniques for location prediction. Lastly, our objective is to assess the adaptive behavior of the LP that is its capability to rapidly detect changes in the movement of the mobile user and react accordingly.

The structure of the paper is as follows: in Section 2 we introduce the proposed adaptive short-memory location predictor model based on local linear regression. Section 3 reports the proposed fuzzy controller for LP and the corresponding mechanism in adaptive location prediction. In Section 4, we assess the proposed LP and the use of the fuzzy controller mechanism. In addition, a performance comparison of our model with other stateful and stateless mobility prediction models is also reported, while Section 5 concludes the paper and reports future trends.

2. Adaptive short-memory location prediction

We adopt a local regression model based on kernel weighted functions in order to determine the future user location through extrapolation. The LP exploits a fuzzy controller in order to decide on the appropriate size of the memory of the local regression model that minimizes the prediction error. This means that, the fuzzy controller adjusts the memory size of the regression model based on the current user mobility behavior. Any detection of change on the mobility behavior is treated through a fuzzy control signal that adjusts the current memory size (history window) of the regression process. The overall model of the proposed LP is illustrated in Fig. 1. Specifically, the regression model accumulates the last $m \geqslant 1$ locations and constructs a statistic regression function f at time instance t. Then, the future location x, which is predicted for the next $l > 1$ time instances (i.e., at time index $t + l$), is an extrapolation point based on the mean value of the user velocity and direction of the last m locations. The prediction error e at time $t + l$ is calculated whenever the predicted location x is not the actual location at time $t + l$. Specifically the prediction error e is the spatial distance between the predicted location and the actual location at time $t + l$. The fuzzy controller is fed with the prediction error e and adjusts the length of the m last locations in the LP.