A Novel Mobility Prediction Algorithm Based on LSVR for Heterogeneous Wireless Networks

Zhenyu Na[1], Yang Cui[2], Yubin Xu[3] and Liming Chen[3]

[1]School of Information Science and Technology, Dalian Maritime University
[2]Institute of Science and Industry Technology, Harbin Institute of Technology
[3]Communication Research Center, Harbin Institute of Technology

nazhenyu@dlmu.edu.cn, ycui@hit.edu.cn, ybxu@hit.edu.cn, liming.chn.hit@gmail.com

Abstract

Mobility prediction algorithm is the significant aspect to improve QoS (Quality of Service) for heterogeneous wireless networks because it decreases handoff latency and preserves resources in arriving cells for users. Since existing mobility prediction algorithms based on GPS (Global Positioning System) often suffer from low prediction accuracy for complex and irregular trajectory, this paper combines support vector regression with local prediction to propose a novel mobility prediction algorithms based on local support vector regression (LSVR) to overcome above deficiency. Simulation results show that LSVR algorithm achieves high prediction accuracy for a size of historical data in three typical mobile scenes.

Keywords: *Mobility prediction algorithm, heterogeneous networks, QoS, local support vector regression*

1. Introduction

Driven by technological developments and industrial interests, existing wireless networks are featured by different client groups and commercial backgrounds and difficult to replace each other. Therefore, the future wireless communication networks will be open and distributed heterogeneous networks comprised of different wireless networks. In such an environment, communication services are highly developed and the number of mobile users is drastically increasing leading to growing shortage of spectrum resources [1]. Meanwhile, mobile users are more eager for seamless and continuous services with strictly guaranteed QoS [2].

Mobility management can coordinate interactions across heterogeneous networks and guarantee the receipt of consistent services for mobile users even when their location continually changes in heterogeneous networks. Mobility prediction is an essentially crucial aspect of mobility management because it can predict user's motion trajectory and preserve required resources by user in the arriving cells to avoid degrading QoS due to insufficient resources. In addition, mobility prediction can partly complete functions of horizontal or vertical handoffs to reduce handoff latency and signaling overhead when user's location is updating. Therefore, well-designed mobility prediction algorithm is highly significant for guaranteeing QoS and maximizing spectrum efficiency.

Analyzing and comparing previous works, this paper proposes a novel mobility algorithm based on local support vector regression (LSVR). By introducing ε – insensitive loss function and applying support vector regression to local prediction, LSVR algorithm can precisely predict complex and irregular trajectory for a small size of historical data.

2. Related Work

Depending on whether GPS is used, mobility prediction algorithms in wireless networks can be classified into two types [3]. One type is without GPS, which uses historical identification (ID) information sequence of cells passed by user as UMH (User Mobile History) and utilizes Markov predictor [4-6], data mining [7] or model matching [8-9] to predict user's trajectory. Though this type of algorithms avoids degrading prediction performances due to bad estimations to the shape and the size of cell, too much historical information should be stored in advance. Further, these algorithms do nothing for new registered users or users without historical information.

The second type of mobility prediction algorithms, which is independent of cell's ID, is different from the first type because it uses GPS to obtain user's coordinate as UMH information, and then uses fitting algorithms to predict user's coordinate or location in the next time. At length, by means of cell boundary estimation algorithm, the cell that user will visit can be determined. Since the second type is different from the first type in implementation scheme, background and condition of applications, the second type is a powerful supplement for the first type.

In recent years, some mobility prediction algorithms of the second type had appeared. Assuming cells are square, [10] proposes that using GPS, the relative distance between a mobile user and its neighbor access points (AP) is periodically monitored, when the distance is less than a certain threshold, the algorithm seems the user visits the cell. But continuous monitoring leads to heavy load and overhead. The mobility prediction algorithm proposed by [11] is only effective for users moving along straight line, not suitable for complex and unknown type of trajectory. [12] proposes a hybrid prediction model, which uses self-organizing feature mapping (SOFM) and multi-layer perceptron network (MLPN) to learn various motion types, and obtains good prediction results. But its flaw is that it needs so much historical information to train off-line that it cannot adapt to dynamic situations. In view of this drawback, [13] applies adaptive resonance theory (ART) to mobility prediction algorithms. Though it can adapt to trajectory of mobile user, it suffers from slow response to fast motion. [14] and [15] utilize auto-regressive model and self-organized characteristic mapping neural network (SOCMNN) to fit user's trajectory, and then predict user's location coordinate.

The common characteristic of above algorithms is that they only pay more their attention to predicting user's coordinate. From the perspective of access management, however, the ultimate task of mobility prediction is to determine which cell will be visited and when. Therefore, after predicting location coordinate, it is also should be determined that the user belongs to which zone according to the shape and the size of the cell. The flaws of above algorithms just lie in assumption about the fixed shape and size of the cell. To cope with situations, some scholars present corresponding solutions [16-18] where [17] is most representative in estimation to the shape and the size of cell.

Though some algorithms based on GPS (the second type) had been much improved, existing algorithms have always suffered from low prediction accuracy for complex trajectory and large amounts of historical motion information. In the light of the defect, this paper proposes a mobility prediction algorithm based on LSVR. Using support vector theory, LSVR algorithm regards the trajectory of mobile user as a function on rectangular plane coordinate system (X-Y plain) and introduces ε -insensitive loss function, and then fits unknown function by means of local information adjacent to the predicted point with high accuracy to achieve precise prediction to user's motion trajectory.

3. Mobility Prediction Algorithm based on LSVR

Support vector theory, which is able to overcome the limited generalization ability due to over-fitting in traditional learning theory, has the unique and globally-optimal solution. Based on support vector machine, support vector regression (SVR) can obtain high prediction accuracy for a small number of samples without local minima by introducing ε – insensitive loss function. As a result, SVR is widely applied to linear and nonlinear predictions [19].

Local prediction is presented relative to global prediction that it means only local information adjacent to the predicted point is used to predict trajectory. On one hand, local prediction can save storage space and improve computational speed. On the other hand, compared with only one global function used, to fit trajectory using multiple local functions can obtain higher prediction accuracy [20].

The basic idea of LSVR mobility prediction algorithm proposed in this paper lies in LSVR applied to trajectory prediction that LSVR algorithm regards trajectory of mobile user as a function on X-Y plain and locally fits the trajectory using SVR. Then, the cell that the user will enter can be determined according to the topology of coverage. At present, it draws much attention that local prediction combined with SVR achieves high prediction accuracy for non-linear prediction problems [21].

3.1. Location Description Unit for Heterogeneous Wireless Networks

Traditionally, user's trajectory is described using cell ID in homogeneous wireless networks because the services and the bandwidth required by the user is independent of the exact location of user in the cell. Therefore, the cell residence time (CRT) and the IDs of cells are used to describe the user's mobility. However, the cell coverage of different wireless networks is quite different form each other, for instance, the cell radium is about 1.5 km for WCDMA networks while the cell radium is roughly 60 m for WLAN. As a result, the traditional method based on cell's ID is not suitable for description of user's location in heterogeneous wireless networks. In view of the disadvantage, overlay coverage zone (OCZ) is introduced to depict user's location in this paper that user's trajectory can be modeled as a series of OCZ' IDs. The classification of OCZ can be according to types of wireless networks which an OCZ covers. In this paper, three-layer OCZ system is introduced, including cellular networks, WMAN (Wireless Metropolitan Area Networks) and WLAN. In this condition, four types of OCZ can be defined and demonstrated as shown in Figure 1.

Type 1: OCZ only covered by cellular networks;

Type 2: OCZ covered by both cellular networks and WMAN;

Type 3: OCZ covered by cellular networks, WMAN and WLAN;

Type 4: OCZ covered by both cellular WLAN.

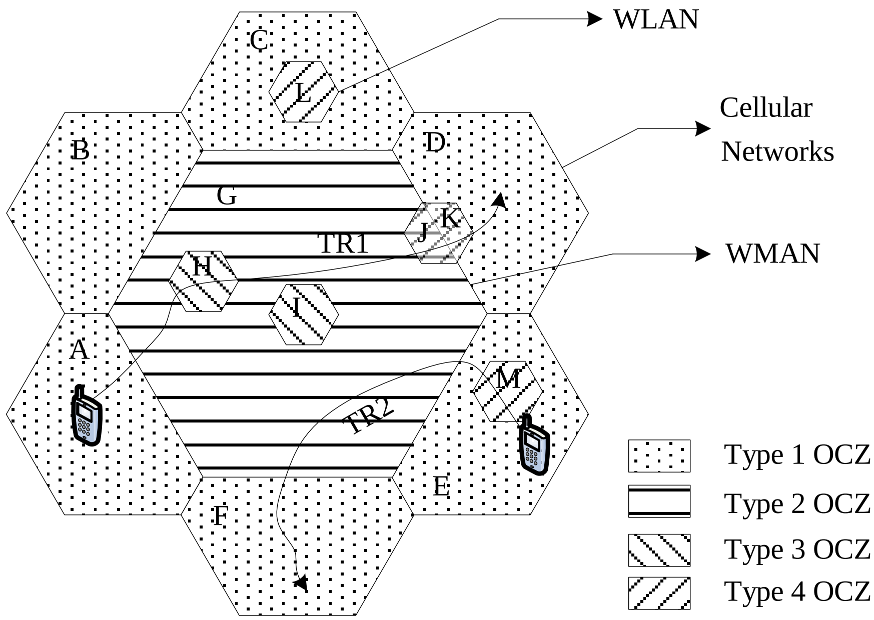

Figure 1. Overlay Coverage Zone

It is worthy to note that there is a WLAN cell divided into J and K parts shown in Figure 1 where part J is together covered by cellular networks, WLAN and WMAN, while part K is covered by both cellular networks and WLAN. The user's trajectory can be represented by a series of OCZ's IDs, for instance, trajectory 1 (TR1) is represented as A-G-H-G-J-K-D, while TR2 is denoted as E-M-E-G-F.

The advantages of using OCZ to describe user's mobility in heterogeneous wireless networks are specially manifested in three aspects. First, OCZ is able to adapt to different wireless networks for different people and flexibly describe the mobility of the terminals. Second, OCZ can well depict the vertical handoffs among different wireless networks. Third, the favorable sensing of multi-mode mobile terminals to electromagnetic environment is the solid foundation of deploying OCZ.

3.2. Local Support Vector Regression

The basic idea of support vector is to find a non-linear mapping in both input and output spaces and then input space is mapped to high dimensional feature space for linear regression [22]. It can be expressed as

$$f(x) = \langle w, \phi(x) \rangle + b \tag{1}$$

where, $\phi(x)$ stands for non-linear mapping function; w represents linear coefficient; b is a real constant; x is the vector in the input space.

In order to solve support vector regression, a risk function should be minimized

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{K}(\xi_i + \xi_i^*) \ \text{ subject to} \begin{cases} y_i - \langle w, \phi(x_i) \rangle - b \le \varepsilon + \xi_i \\ \langle w, \phi(x_i) \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{2}$$

where, ξ_i (ξ_i^*) represents the floor (ceiling) of training error, $\frac{1}{2}\|w\|^2$ stands for normalized unit, C is normalized constant that means the degree of compromise between smoothness and accuracy for the function f .

As shown in Figure 2, formula (3) means training data x_i are mostly located in the zone of ε . If x_i are out of the zone of ε , it will be punished in a linear fashion. SVR minimizes $\frac{1}{2}\|w\|^2$ and $C\sum_{i=1}^{K}(\xi+\xi^*)$ to avoid over-fitting or under-fitting for training data.

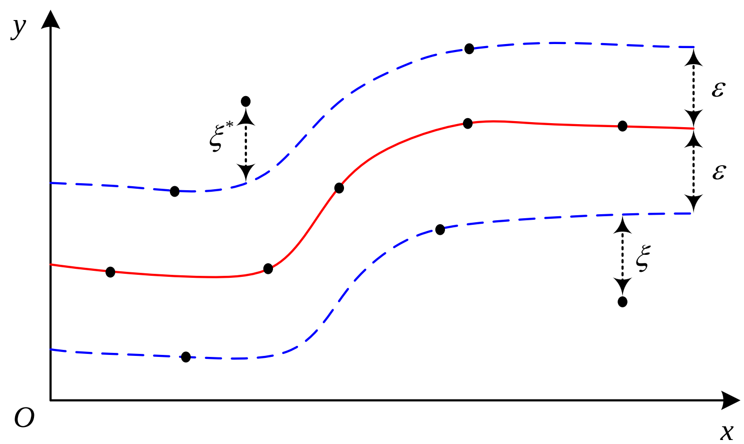

Figure 2. ε **-insensitive Tube for SVR**

Introducing Lagrange multipliers α and α^* (satisfying $\alpha_i\alpha_i^*=0$ and $\alpha_i,\alpha_i^*\geq 0$, for $i=1,\cdots,K$), (2) can be turned into a convex quadratic optimization problem according to Karush-Kuhn-Tucker optimization conditions [23]

$$\min\left\{\frac{1}{2}\sum_{i,j=1}^{K}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)Q(x_i,x_j)+\varepsilon\sum_{i=1}^{K}(\alpha_i+\alpha_i^*)-\sum_{i=1}^{K}y_i(\alpha_i-\alpha_i^*)\right\}$$
$$\text{Subject to }\sum_{i=1}^{K}(\alpha_i-\alpha_i^*)=0\text{ and }0\leq\alpha_i,\alpha_i^*\leq C \tag{3}$$

where $Q(x_i,x_j)$ is kernel function which is the inner product of $\phi(x_i)$ and $\phi(x_j)$.

By means of kernel functions, all of computations can be directly completed in the input space without knowing definite $\phi(x)$. The selection of kernel function is highly important to the performance of SVR algorithm. In this paper, Gaussian kernel is selected mainly because compared with other types of kernel functions, Gaussian kernel can increase prediction accuracy by 8.91%-10.43%for complex and irregular predictions [22]. The definition of Gaussian kernel is given by

$$Q(x_i,x)=\exp\left(-\frac{\|x_i-x\|^2}{2\sigma^2}\right) \tag{4}$$

The regression output is

$$\hat{f}(x) = \sum_{i=1}^{K} (\alpha_i - \alpha_i^*) Q(x_i, x) + b \tag{5}$$

Local prediction means that only a part of training data is used to find locally fitting function $\hat{f}$. In this paper, K training data adjacent to the predicted point are used to find $\hat{f}$ and then give the predicted trajectory.

3.3. Implementation of LSVR Algorithm

As user's location can be represented by two-dimensional coordinate (x, y), the user's trajectory can be viewed as the curve of a function f on the X-Y plain, i.e. $y = f(x)$ or $x = f(y)$. In order to predict user's location in the next time t, the coordinate value of x or y should be solved according to fitting function $\hat{f}$. As there is no time variable in function f, (2) and (3) can be used to determine on which axis (X or Y axis) the change of user's trajectory in K intervals is smaller, and then the coordinate of the determined axis is seemed as the variable of the other coordinate. For example, if the change on X axis of the trajectory's curve is smaller, the functional form is $y = f(x)$. Further, $\hat{f}(x)$ or $\hat{f}(y)$ can be derived by means of vector regression and then the next time can be estimated using extrapolation. Finally, the estimated time is substituted into the fitting function to calculate the other coordinate. The concrete steps of LSVR algorithm are presented below.

Step 1: To calculate $\Delta x(K)$ and $\Delta y(K)$:

$$\Delta x(K) = \frac{1}{K-1} \sum_{i=2}^{K} \left(x(i) - x(i-1) \right) = \frac{1}{K-1} \left(x(K) - x(1) \right) \tag{6}$$

$$\Delta y(K) = \frac{1}{K-1} \sum_{i=2}^{K} \left(y(i) - y(i-1) \right) = \frac{1}{K-1} \left(y(K) - y(1) \right) \tag{7}$$

Step 2: If $\Delta x(K) < \Delta y(K)$, it means the change on X-axis is smaller than that on Y-axis, and the algorithm goes to Step 3; If $\Delta x(K) > \Delta y(K)$, it indicates the change on Y-axis is smaller than that on X-axis, and the algorithm directly goes to Step 4. If $\Delta x(K) = \Delta y(K)$, two cases should be discussed: (1) when $\Delta x(K) = \Delta y(K) \neq 0$, the algorithm randomly selects Step 3 or Step4; (2) when $\Delta x(K) = \Delta y(K) = 0$, it means the user either does not move or comes back to where it departs, so LSVR algorithm reset K and then rerun Step 2 according to the real situation.

Step 3: Let y be a function of x. The fitting function $y = \hat{f}(x)$ is calculated using K historical data (x_k, y_k) for $k = i-K+1, i-K, \cdots, i$; If $\hat{x}(i+1)$ denotes the estimated value of $\hat{x}(i+1)$ in next time $(i+1)$, $\hat{x}(i+1)$ can be extrapolated as $\hat{x}(i+1) = x(i) + \Delta x(K)$ and then $\hat{x}(i+1)$ is substituted into $\hat{f}$ to get $\hat{y}(i+1) = \hat{f}(\hat{x}(i+1))$.

Step 4: Let x be a function of y. The fitting function is $x = \hat{f}(y)$. Similar to Step 3, $\hat{y}(i+1)$ can be extrapolated as $\hat{y}(i+1) = \hat{y}(i) + \Delta y(K)$ and $\hat{x}(i+1) = \hat{f}(\hat{y}(i+1))$.

Compared with algorithms without GPS, the shape and the size of OCZ for algorithms with GPS are indispensable when the prediction algorithm determines where the predicted location is located. In general, the shape and the size of OCZ are highly dependent on the minimum cell among the cells of different networks. However, the shape and the size of each cell are time-varying for different networks leading to OCZ being dynamic. Presently, as some prediction algorithms suppose the shape and the size fixed [14,24] more often than not, their prediction results are often limited or deteriorated. Fortunately, there have already been several methods recently to overcome the drawback. For example, [17] utilizes BAPs (Boundary Approximation Points) to estimate the real shape and size of a cell and obtains satisfactory effect. Therefore, based on such algorithms, LSVR mobility prediction algorithm proposed in this paper is theoretically feasible.

4. Simulation Results and Analyses

Simulation scenes are the same as Figure 1. CPP (Correct Prediction Probability) serves as the metric to evaluate performances of the LSVR algorithm. CPP is defined as

$$P_R = \frac{\left|\{(x^{'},y^{'}):\left\|(x,y)-(x^{'},y^{'})\right\| \le R\}\right|}{N} \tag{8}$$

where R is the radium threshold; N is the times of prediction. The top half of the right side in (8) indicates the prediction times that the difference between the predicted location and the real location is less than R, while (8) stands for the probability that the difference between the predicted location and the real location is less than R.

In order to investigate the relationship between R and the CPP, LSVR mobility algorithm is applied to three typical mobile scenes, including inter-city zone (OCZ Type 1), sub-ciy zone (OCZ Type 2) and hop spot zone (OCZ Type 3 and 4). The size of historical data is set to 12 and 6, respectively. The comparison of CPP under different scenes and size of historical data is demonstrated in Figure 3. It is very obvious that CPP increases with the increasing radium threshold R for different scenes, especially when R is more than 18m, all CPPs for different scenes and data size are near to 1. Also, it is apparent that for all of simulation scenes, CPPs are quite different for the same size of historical data. For example, when $R = 6$m and $K = 6$, CPPs are 0.95, 0.84 and 0.88 for inter-city zone, sub-city zone and intra-city hot spot, respectively. Only considering the inter-city zone, the CPP (=0.98) with $K = 12$ is larger than the CPP (=0.95) with $K = 6$. In this sense, to achieve higher CPP, the size of historical data should be set according to different mobile scenes.

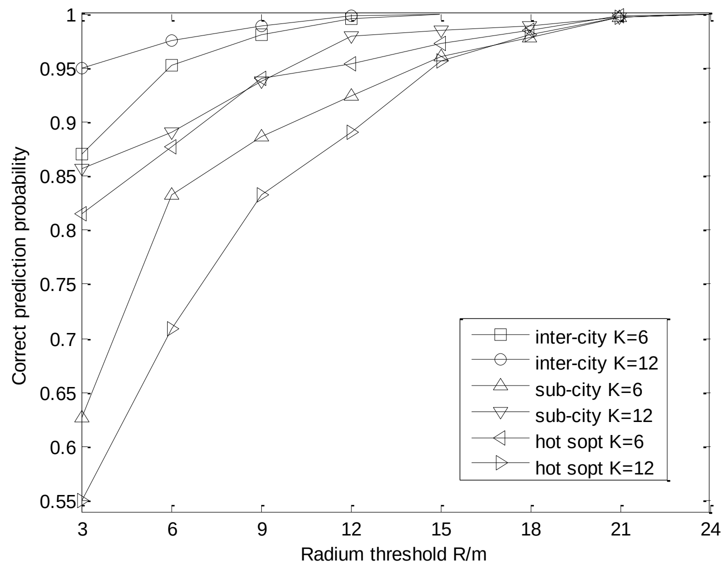

Figure 3. Correct Prediction Probability vs. Radium Threshold (R)

Two typical prediction algorithms, which are the mobility algorithm based on ARIMA [25] and the ART based mobility prediction algorithm [13], are used to compare CPP with LSVR mobility prediction algorithm. Three algorithms are simulated for $R = 5$m in above three scenes and the simulation results are shown in Figures 4, 5 and 6, respectively.

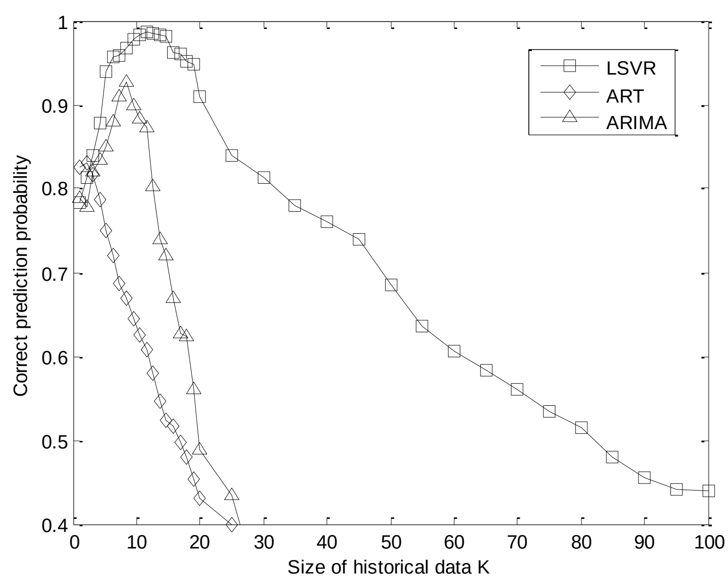

Figure 4. Correct Prediction Probability of Three Algorithms vs. Data Size K for Inter-city Zone

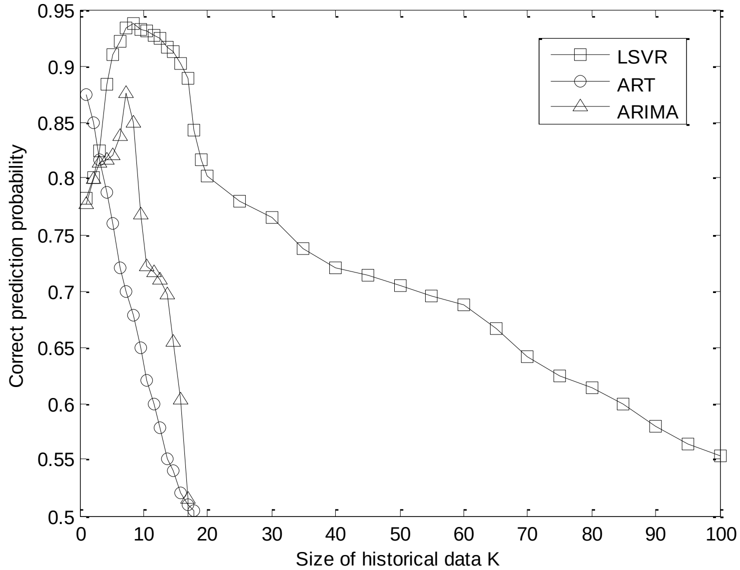

Figure 5. Correct Prediction Probability of Three Algorithms vs. Data Size K for Sub-city Zone

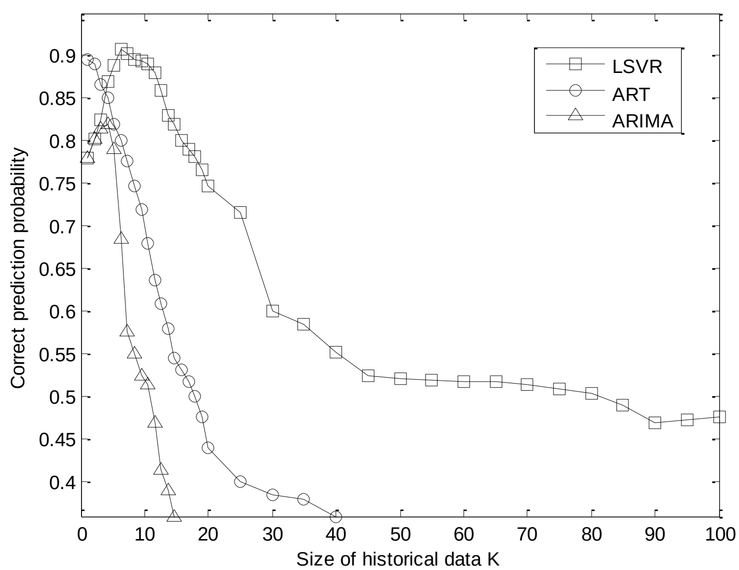

Figure 6. Correct Prediction Probability of Three Algorithms vs. Data Size K for Intra-city Hot Spot

From Figures 4, 5 and 6, it can be easily seen that the maximum CPP of LSVR algorithm for different scenes is sequentially decreasing with the values 0.981, 0.946 and 0.905, respectively, mainly because the trajectory's complexity and irregularity for three scenes is gradually increasing. Compared with the prediction algorithm based on ARIMA, LSVR algorithm has higher accuracy for all of three scenes due to support vector regression applied to local information prediction. Especially for intra-city hot spot, LSVR algorithm has a significant advantage over ARIMA algorithm in prediction of complex and irregular trajectory. For ART based algorithm, as it uses resonance theory and matching technology to prediction trajectory, the more the mobile historical information for matching is, the more accurate the predicted results are. When the information is not enough, however, the predicted result of ART based algorithm highly deteriorates. Compared with ART based algorithm, LSVR algorithm has higher maximum CPP than the former in both inter-city and sub-city zones, but its maximum CPP is close to the former in intra-city hot spot. Since user has highly random mobility in intra-city hot spot, ART based algorithm has more trajectory matching types relative to LSVR algorithm for the same size of historical GPS information. When it comes to inter-city and sub-city cases, as these scenes are so simple that there are either very few or no trajectory matching types, ART based algorithm has relatively lower CPP. Therefore, LSVR mobility prediction algorithm proposed in this paper has satisfactory performance.

In addition, according to Figures 4, 5 and 6, it is not difficult to observe that the size of historical data is different for different scenes when CPP achieves the maximum value. Concretely, in the context of this paper, K^* are 12, 9 and 7 for inter-city, sub-city and intra-city cases, respectively. When user is located in inter-city zone, as its speed is relatively high and less changed, more historical data is helpful to improve CPP. For the user in a city, its speed and direction are often randomly and frequently changed due to irregular trajectory; therefore, the size of historical data is very small and CPP is inferior to inter-city case. Since sub-city zone is between the former two cases, its CPP performance is between the former two cases. In fact, as user would successively go through multiple mobility scenes in heterogeneous wireless networks, the predefined and fixed size of historical data information is bound to affect the performance of mobility prediction. Therefore, the future work will focus on the adaptive and optimized selection of the data size.

5. Conclusion

Since existing mobility prediction algorithms based on GPS can not well cope with unknown and irregular mobile trajectory resulting in unsatisfactory prediction accuracy, a novel mobility prediction algorithm based on local support vector regression (LSVR) is proposed. On one hand, unknown trajectory can be effectively predicted by means of fitting methodology. On the other hand, the prediction accuracy is further improved using support vector regression in local information. Simulation results show that for three typical cases, LSVR algorithm achieves higher correct prediction probability than ARIMA and ART based algorithms. In the end, some prospects of the future work are given.

Acknowledgements

This paper is supported by both National Basic Research Program of China - 973 (No. 2007CB310606) and Fundamental Research Funds for the Central Universities of China.

The faculty of Communication Research Center at Harbin Institute of Technology gives many constructive suggestions to the algorithm designs and simulations.

References

[1] P. Leaves, K. Moessner, R. Tafazolli, D. Grandblaise, D. Bourse, R. Tonjes and M. Breveglieri, “Dynamic Spectrum Allocation in Composite Reconfigurable Wireless Network”, IEEE Communications Magazine, vol. 42, **(2004)**, pp. 5.

[2] Q. Du and X. Zhang, "Statistical QoS Provisionings for Wireless Unicast/multicast of Multi-Layer Video Streams", IEEE Journal on Selected Areas in Communications, vol. 28, **(2010)**, pp. 3.
[3] M. Ni, Z. Zhong and D. Zhao, "MPBC: a Mobility Prediction-Based Clustering Scheme for Ad Hoc Networks", IEEE Transactions on Vehicular Technology, vol. 60, **(2011)**, pp. 9.
[4] L. Song, D. Kotz, R. Jain and X. He, "Evaluating Location Predictors with Extensive Wi-Fi Mobility Data", Proceedings of IEEE INFOCOM'04, 23rd Annual Joint Conference of the IEEE Computer and Communications Societies, **(2004)** March 7-11; Hong Kong, China.
[5] L. Song, D. Kotz, R. Jain and X. He, "Evaluating Next-Cell Predictors with Extensive Wi-Fi Mobility Data", IEEE Transactions on Mobile Computing, vol. 5, **(2006)**, pp. 12.
[6] L. Song, U. Deshpande, U. C. Kozat, D. Kotz and R. Jain, "Predictability of WLAN Mobility and its Effects on Bandwidth Provisioning", Proceedings of IEEE INFOCOM'06, **(2006)** April, 19-25; Rio de Janeiro, Brazil.
[7] F. Yu and V. C. M. Leung, "Mobility-Based Predictive Call Admission Control and Bandwidth Reservation in Wireless Cellular Networks", Proceedings of IEEE INFOCOM'01 20th Annual Joint Conference of the IEEE Computer and Communications Societies, **(2001)** April 22-26; Alaska, USA.
[8] J. G. Cleary, W. J. Teahan and I. H. Witten, "Unbounded Length Contexts for PPM", Proceedings of IEEE Data Compression Conference, **(1995)** March 28-30; Snowbird, Utah.
[9] P. Jacquet, W. Szpankowski and I. Apostol, "A Universal Predictor Based on Pattern Matching", IEEE Transactions on Information Theory, vol. 48, **(2002)**, pp. 6.
[10] H. -W. Ferng, W. -Y. Kao, D. Shiung, C. -L. Liu, H. -Y. Chen and H. -Y. Gu, "A Dynamic Resource Reservation Scheme with Mobility Prediction for Wireless Multimedia Networks", Proceedings of IEEE VTC2004-Fall, **(2004)** September 26-29; Los Angeles, USA.
[11] B. Liang, Z. J. Haas, "Predictive Distance-Based Mobility Management for Multidimensional PCS Networks", IEEE/ACM Transactions on Networking, vol. 11, **(2003)**, pp. 5.
[12] K. Majumdar and N. Das, "Mobile User Tracking Using a Hybrid Neural Network", Wireless Networks, Springer, vol. 11, **(2003)**, pp. 3.
[13] T. Anagnostopoulos, C. Anagnostopoulos and S. Hadjiefthymiades, "An Online Adaptive Model for Location Prediction", Autonomic Computing and Communications Systems, vol. 23, **(2010)**, pp. 1.
[14] Z. R. Zaidi and B. L. Mark, "Mobility Estimation for Wireless Networks Based on an Autoregressive Model", Proceedings of IEEE GLOBECOM'04, **(2004)** 29 November- 3 December; Dallas, TX, USA.
[15] M. -H. Park, J. -H. Hong and S. -B. Cho, "Two-Stage User Mobility Modeling for Intention Prediction for Location-Based Services", Lecture Notes in Computer Science, Springer, vol. 4224, **(2006)**.
[16] S. Intarasothonchun, S. Thipchaksuratan and R. Varakulsiripunth, "Effect of Mobility on Predictive Mobility Support Dynamic Resource Reservation in Cellular Networks", Proceedings of 8th International Conference on ITS Telecommunications, **(2008)** October 22-24; Hilton Phuket, Thailand.
[17] H. -W. Ferng, W. -Y. Kao, D. Shiung, C. -L. Liu, H. -Y. Chen and H. -Y. Gu, "A Dynamic Resource Reservation Scheme with Mobility Prediction for Wireless Multimedia Networks", Proceedings of IEEE VTC2004-Fall, **(2004)** September 26-29; Los Angeles, USA.
[18] P. Fazio, F. De Rango and I. Selvaggi, "A Novel Passive Bandwidth Reservation Algorithm Based on Neural Networks Path Prediction in Wireless Environments", Proceedings of International Symposium on Performance Evaluation of Computer and Telecommunication Systems (SPECTS), **(2010)** July 11-14; Ottawa, Canada.
[19] C. Chang and C. Lin, "A Library for Support Vector Machines", ACM Transactions on Intelligent Systems and Technology, vol. 2, **(2011)**, pp. 3.
[20] K. W. Lau and Q. H. Wu, "Local Prediction of Non-Linear Time Series Using Support Vector Regression", Journal of Pattern Recognition, vol. 41, **(2008)**, pp. 5.
[21] E. E. Elattar, J. Goulermas and Q. H. Wu, "Electric Load Forecasting Based on Locally Weighted Support Vector Regression", IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews, vol. 40, **(2010)**, pp. 7.
[22] A. J. Smola and B. Scholkopf, "A Tutorial on Support Vector Regression", Journal of Statistics and Computing, vol. 14, **(2004)**, pp. 3.
[23] V. N. Vapnik, "Statistical Learning Theory", New York, John Wiley & Sons, Inc., **(1998)**.
[24] S. Akoush and A. Sameh, "The Use of Bayesian Learning of Neural Networks for Mobile User Position Prediction", Proceedings of 17th International Conference on Intelligent Systems Design and Applications, **(2007)** June 21-23; Maribor, Slovenia.
[25] M. Zhou, Z. Yan, Y. X. Ni, G. Li and Y. Nie, "Electricity Price Forecasting with Confidence-Interval Estimation Through an Extended ARIMA Approach", IEE Proceedings of Generation, Transmission and Distribution, vol. 153, **(2006)**, pp. 2.

Authors

Zhenyu Na

Zhenyu Na was born in 1981, Harbin, P.R.China. He received the B.S. degree in communication engineering, M.S. degree in information and communication engineering from Harbin Institute of Technology (HIT) in 2004 and 2007, respectively. In 2010, he received doctoral degree in information and communication engineering at Communication Research Center of HIT.

Now, he is a lecturer at School of Information Science and Technology of Dalian Maritime University (DMU) with research interests including satellite communications and networks, wireless networks, MIMO-OFDM communications. Until now, he has published more than 10 papers in famous international journals and conferences.

Yang Cui

Yang Cui was born in 1982, Harbin, P.R.China. He received the B.S. degree in communication engineering, M.S. degree in information and communication engineering from Harbin Institute of Technology (HIT) in 2005 and 2007, respectively. In 2012, he received doctoral degree in information and communication engineering at Communication Research Center of HIT.

Now, he is an assistant professor at Institute of Science and Industry Technology of HIT. His research interests cover wireless communications and networks, QoS, radio resource management for heterogeneous wireless networks. Until now, he has published more than 10 papers in international journals and conferences.