A Fuzzy Decision Tree Based Mobility Prediction Mechanism in Mobile Internet

(Invited Paper)

Xingwei Wang[1], Shuxiang Cai[1], Hui Cheng[2], Min Huang[1], Jiannong Cao[2]
1. College of Information Science and Engineering, Northeastern University, Shenyang, 110004, China
wangxw@mail.neu.edu.cn
2. Department of Computing, Hong Kong Polytechnic University, Hong Kong, China

Abstract

Considering environment factor and user movement randomness, a fuzzy decision tree based mobility prediction mechanism in mobile Internet is proposed. Based on the instance set, an initial fuzzy decision tree is built up with fuzzy attribute and classification entropy. The tree produces fuzzy decision rules for instant mobility predictions and evolves with time. Simulation results have shown that the proposed mechanism is both feasible and effective with relatively high accuracy and low overhead of mobility prediction.
Keywords: mobile Internet, mobility prediction, fuzzy decision tree

1 Introduction

In mobile Internet, predicting the target cell and doing resource reservation is often an effective way to guarantee the communication QoS (Quality of Service) to the MU (Mobile User) during the handoff [1], due to the unreliable wireless channels and their limited bandwidths. The accuracy on mobility prediction to the MU has significant influence on the degree of QoS guarantee [2].

Usually, the landforms, roads and buildings in a cell are rarely changed, thus mobility prediction to the MU can be performed. However, due to the randomness of the MU movement, it is very difficult to achieve accurate prediction. Existing mobility prediction mechanisms can be roughly divided into three classes. For the first class, the signals of surrounding cells received by the MU or the signals of the MU received by surrounding cells are monitored. For example, in [3], the cell of which signal intensity is the strongest is selected as the target one; however, the negative influence of the surrounding barrier and multipath fade effect on the prediction accuracy is serious. Some improvements have been made in [4], the cell with the highest defined channel quality rather than the simple signal intensity is selected as the target one, and the bad influence of multipath fade effect is overcome to some degree, however, the surrounding cell cooperation is necessary when doing the mobility prediction to the MU. In [5], the randomness of the MU movement is taken into account, and based on the multi-target prediction method, one or even multiple target cells are determined, getting the higher prediction accuracy with the higher overhead. For the second class, the motion probability model is adopted. For example, in [6], the MU velocity is determined according to the intensities of signals received by its current and surrounding cells; based on its proposed motion probability model, the probability of entering into each surrounding cell is calculated, and then the target cell is determined; however, the influence of velocity on motion diversion is not taken into account. In [7], based on its proposed motion probability model, the cells in the predicted fan-shaped piece are selected as the target ones with the influence of velocity on motion diversion considered, however, the overhead is higher. For the third class, the MU geographic location information is used to make mobility prediction. For example, In [8], GPS (Global Positioning System) [8] is used to collect the MU position information periodically, and then the target cell is determined, however, the influence of the MU movement randomness on the prediction accuracy is not considered sufficiently.

In this paper, a fuzzy decision tree based mobility prediction mechanism is proposed, trying to improve prediction accuracy with reduced overhead. Simulation results have shown that it is both feasible and effective.

* This work is supported by Program for New Century Excellent Talents in University; the National Natural Science Foundation of China under Grant No. 60473089; the National Development and Reform Commission under CNGI-04-13-2T, CNGI-04-6-2T and CNGI-04-15-7A.

2 Fuzzy decision tree

Decision tree [9] is built up on instance set, and is based on certain heuristic information to make prediction. The ID3 algorithm [9-11] is one of the most popular algorithms used in decision tree with the classification entropy as the heuristic variable. It selects the attribute with the smallest entropy as the extended one to minimize the class chaos degree, and thus a clear decision tree is formed. However, a lot of things in reality are difficult to be exactly described, therefore the so called fuzzy decision tree [9-11] is presented.

Domain $X=\{e_1,e_2,...,e_n\}$ represents the instance set, from which the prediction rules are derived, and the value of n is determined according to the actual situation. $e_k\left(k=1,2,...,n\right)$ has the following attributes: $A^{(1)}$, $A^{(2)}$,..., $A^{(s)}$, and $A^{(s)}$ is the classification attribute, representing the objective to be predicted. For any $A^{(i)}\left(i=1,2,...,s-1\right)$, there is a corresponding attribute description set $T\left(A^{(i)}\right)=\left\{T_1^{(i)},T_2^{(i)},...,T_{m_i}^{(i)}\right\}$. For any $T_j^{(i)}\left(j=1,2,...,m_i\right)$, there is a fuzzy set defined on X. The membership degree function of e_k to $\mathrm{T_j}\left(\mathrm{A}^{(i)}\right)$ is denoted by $\mu_{ij}\left(e_k\right)$, and then

$$\mathrm{T_j}\left(\mathrm{A}^{(i)}\right)=\frac{\mu_{ij}\left(e_1\right)}{e_1}+\frac{\mu_{ij}\left(e_2\right)}{e_2}+...+\frac{\mu_{ij}\left(e_n\right)}{e_n}\text{ [11].}$$

3 Fuzzy decision tree based mobility prediction mechanism

The usual cell layout in mobile Internet is shown in Fig.1. If one MU in cell 0 will handoff, the target cell must be one of the cells 1-6. The MU handoff histories from cell 0 to cells 1-6 constitute the instance set necessary for the initial fuzzy decision tree construction for cell 0. In the proposed mechanism, based on the instance set, an initial fuzzy decision tree is built up to predict the handoff target cell(s), and is modified online according to the tree maintenance criteria.

3.1 Initial fuzzy decision tree construction

3.1.1. Attribute setup: There are 6 classes and totally 11 attributes being setup, that is, $s=11$.

① $A^{(1)}$ It is the MU's position just before the handoff, denoted by $<r$, $\alpha>$ (here, r is the radius and α is the angle). As shown in Fig.2, the MU handoffs at the boundary of the cell, thus $A^{(1)}$ can be determined according to r and α.

② $A^{(2)}$ It is the MU's handoff time. According to the actual prediction accuracy requirement, microsecond, millisecond or second, etc., can be used as the timing unit.

③ $A^{(3)}$ It is the MU's instant movement speed along the radius direction at the time of handoff occurred, denoted by $\left|v_r\right|$.

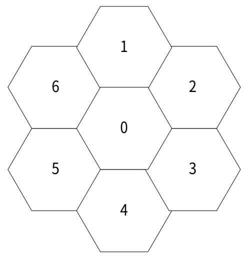

Fig.1. **Cell layout in mobile Internet**

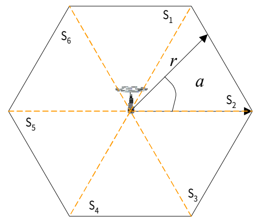

Fig.2. **Position just before handoff**

④ $A^{(4)}$ It is the MU's QoS requirement level based on DiffServ [12].

⑤ $A^{(5)}$, $A^{(6)}$, $A^{(7)}$, $A^{(8)}$, $A^{(9)}$ and $A^{(10)}$ They are the signal intensities of 6 surrounding cells received by the MU.

⑥ $A^{(11)}$ It is the MU's position just after the handoff, and is the classification attribute. As shown in Fig.1, if the MU is in the cell 0 before handoff, $A^{(11)}$ is <cell 1, cell 2, cell 3, cell 4, cell 5, cell 6>.

3.1.2. Attribute fuzziness: Among the above 11 attributes, $A^{(11)}$ is the classification criterion and the predicted objective for the fuzzy decision tree. It should not be fuzzy. However, the other 10 attributes should be used to classify the instance set fuzzily according to their corresponding attribute description sets.

$A^{(1)}$ has m_1 = 6 attribute descriptions. Each edge of hexagon has one corresponding sector (see Fig.2). $T\left(A^{(1)}\right)=\left\{T_1^{(1)},T_2^{(1)},T_3^{(1)},T_4^{(1)},T_5^{(1)},T_6^{(1)}\right\}$={S1, S2, S3, S4, S5, S6}, and the corresponding membership degree functions $\mu_{11}\left(\alpha\right)$, $\mu_{12}\left(\alpha\right)$, $\mu_{13}\left(\alpha\right)$, $\mu_{14}\left(\alpha\right)$, $\mu_{15}\left(\alpha\right)$, $\mu_{16}\left(\alpha\right)$ are shown in Fig.3.

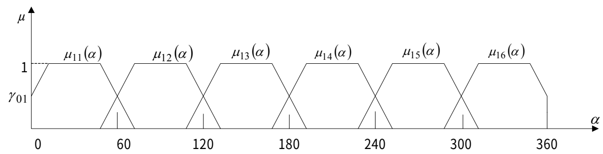

Fig.3. **Fuzziness of** $A^{(1)}$

$A^{(2)}$ has m_2 attribute descriptions and the value of m_2 is determined based on the actual situation and prediction accuracy requirement, that is, $T\left(A^{(2)}\right)=\left\{T_1^{(2)},T_2^{(2)},...,T_{m_2}^{(2)}\right\}$ ={t1, t2,..., tm2}, for example, {8:00:00, 9:00:00, ..., 22:00:00}. Suppose t is the time variable, and the corresponding membership degree functions $\mu_{21}\left(t\right)$, $\mu_{22}\left(t\right)$,..., $\mu_{2m_2}\left(t\right)$ are shown in Fig.4.

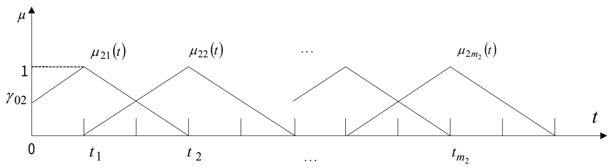

Fig.4. **Fuzziness of** $A^{(2)}$

$A^{(3)}$ has m_3 attribute descriptions and the value of m_3 is determined based on the actual situation and prediction accuracy requirement, that is, $T\left(A^{(3)}\right)=\left\{T_1^{(3)},T_2^{(3)},...,T_{m_3}^{(3)}\right\}$ ={V1, V2,..., Vm3}, V1<V2…<Vm3, and the corresponding membership degree functions $\mu_{31}\left(\left|v_r\right|\right)$, $\mu_{32}\left(\left|v_r\right|\right)$,..., $\mu_{3m_3}\left(\left|v_r\right|\right)$ are shown in Fig.5.

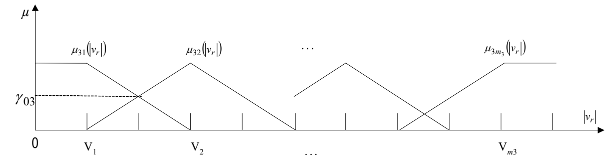

Fig.5. **Fuzziness of** $A^{(3)}$

$A^{(4)}$ has $m_4=Q$ attribute descriptions, that is, $T\left(A^{(4)}\right)=\left\{T_1^{(4)},T_2^{(4)},...,T_{m_4}^{(4)}\right\}$ ={1, 2, ..., Q }, Q is the highest QoS level, 1 is the lowest one. The corresponding membership degree functions μ_{41}, μ_{42} ,..., μ_{4m_4} are shown in Fig.6.

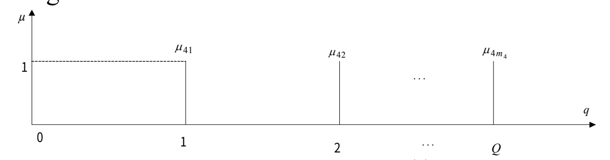

Fig.6. **Fuzziness of** $A^{(4)}$

$A^{(5)}$, $A^{(6)}$, $A^{(7)}$, $A^{(8)}$, $A^{(9)}$, $A^{(10)}$ have m_5, m_6, m_7, m_8, m_9, m_{10} attribute descriptions respectively, that is, $T\left(A^{(l)}\right)=\left\{T_1^{(l)},T_2^{(l)},...,T_{m_l}^{(l)}\right\}$ ={I_{l1}, I_{l2}, ...,I_{lm_l} } (l=5,6,7,8,9,10), I_{l1}< I_{l2}...<I_{lm_l}. Their values are determined based on the actual situation and prediction accuracy requirement and in increasing order. Suppose is_l is the signal intensity variable, the corresponding membership degree functions $\mu_{l1}\left(is_l\right)$, $\mu_{l2}\left(is_l\right)$,..., $\mu_{lm_l}\left(is_l\right)$ are shown in Fig.7.

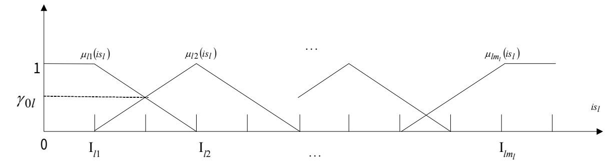

Fig.7. **Fuzziness of** $A^{(l)}$

3.1.3. Fuzzy classification entropy: According to [13], the following definitions are given:

Definition 1: the potency of $T_j\left(A^{(i)}\right)$ is

$$M_j\left(A^{(i)}\right)=\sum_{k=1}^{n}\mu_{ij}\left(e_k\right).$$

Definition 2: the relative frequency of $T_j^{(i)}$ corresponding to the kth ($1\le k\le 6$) value of $A^{(11)}$ is

$$p_{jk}^{(i)}=\frac{M\left(T_j\left(A^{(i)}\right)\cap T_k\left(A^{(s)}\right)\right)}{M\left(T_j\left(A^{(i)}\right)\right)}.$$

Definition 3: the classification entropy of $T_j^{(i)}$ is

$$entropy_j^{(i)}=\sum_{k=1}^{m_i}-p_{jk}^{(i)}\log_2 p_{jk}^{(i)}.$$

Definition 4: the average classification entropy of $A^{(i)}$ is $E^{(i)}=\sum_{j=1}^{m_i}\frac{M\left(T_j\left(A^{(i)}\right)\right)}{\sum_{j=1}^{m_i}M\left(T_j\left(A^{(i)}\right)\right)}entropy_j^{(i)}$.

3.1.4. Initial fuzzy decision tree construction procedure: It is described as follows:

Step1. Make all elements in the instance set to be fuzzy;

Step2. Select the attribute with the smallest $E^{(i)}$ as the root node attribute in fuzzy decision tree, and regard the root node as the current node;

Step3. In each fuzzy set corresponding to every attribute description of the current node attribute, select those elements of which membership degree function values are larger than the preset threshold γ ($0<\gamma\le\gamma_{0h}$, h=1,2,3,5,6,7,8,9,10, see Fig.3, Fig.4, Fig.5 and Fig.7) to form the fuzzy subclass set, and each such set is considered as one child node of the current node;

Step4. For each child node of the current node, if each element of its fuzzy subclass set has the same classification attribute value, or all the attributes of the nodes along the branch from the root node to the current node have been used, mark it as the leaf node. If all of its child nodes have been marked as the leaf nodes, the procedure ends; otherwise, select the unused attribute with the smallest $E^{(i)}$ as the child node attribute and regard the child node as the current node, goto Step3.

One example fuzzy decision tree produced by the proposed procedure is shown in Fig.8.

3.2 Mobility prediction mechanism

3.2.1. Fuzzy rules: Definition 5 [11]: suppose A and B are fuzzy sets defined on domain X, "IF A THEN B" is called a fuzzy rule, denoted by "A→B", A being the condition fuzzy set and B being the conclusion fuzzy set.

According to definition 5, one fuzzy decision tree can be transformed into a lot of fuzzy decision rules. Each leaf node is corresponding to one fuzzy rule. For example, the fuzzy decision tree in Fig.8 can be transformed into the following 10 fuzzy rules:

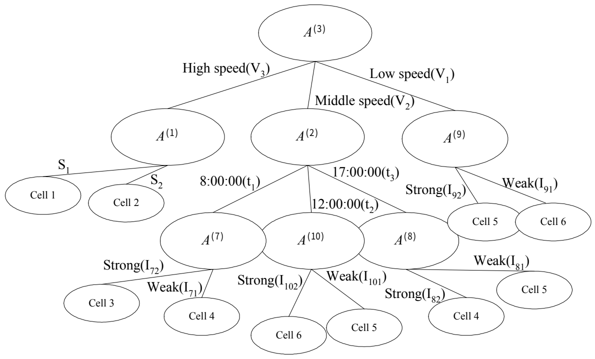

Fig.8. **Example of fuzzy decision tree**

Rule 1: IF $A^{(1)}$ belongs to "S1" (namely $\mu_{11}(\alpha)>\gamma$) AND $A^{(3)}$ belongs to "high speed (V_3)" (namely $\mu_{33}(v)>\gamma$) THEN $A^{(11)}$ belongs to "cell 1".

Rule 2: IF $A^{(1)}$ belongs to "S2" (namely $\mu_{12}(\alpha)>\gamma$) AND $A^{(3)}$ belongs to "high speed (V_3)" (namely $\mu_{33}(v)>\gamma$) THEN $A^{(11)}$ belongs to "cell 2".

Rule 3: IF $A^{(2)}$ belongs to "8:00:00(t1)" (namely $\mu_{21}(t)>\gamma$) AND $A^{(3)}$ belongs to "middle speed (V_2)" (namely $\mu_{32}(v)>\gamma$) AND $A^{(7)}$ belongs to "strong(I_{72})" (namely $\mu_{72}(rs_3)>\gamma$) THEN $A^{(11)}$ belongs to "cell 3".

Rule 4: IF $A^{(2)}$ belongs to "8:00:00(t1)" (namely $\mu_{21}(t)>\gamma$) AND $A^{(3)}$ belongs to "middle speed (V_2)" (namely $\mu_{32}(v)>\gamma$) AND $A^{(7)}$ belongs to "weak(I_{71})" (namely $\mu_{71}(rs_3)>\gamma$) THEN $A^{(11)}$ belongs to "cell 4".

Rule 5: IF $A^{(2)}$ belongs to "12:00:00(t_2)" (namely $\mu_{22}(t)>\gamma$) AND $A^{(3)}$ belongs to "middle speed (V_2)" (namely $\mu_{32}(v)>\gamma$) AND $A^{(10)}$ belongs to "strong(I102)" (namely $\mu_{102}(rs_6)>\gamma$) THEN $A^{(11)}$ belongs to "cell 6".

Rule 6: IF $A^{(2)}$ belongs to "12:00:00(t2)" (namely $\mu_{22}(t)>\gamma$) AND $A^{(3)}$ belongs to "middle speed (V_2)" (namely $\mu_{32}(v)>\gamma$) AND $A^{(10)}$ belongs to "weak(I_{101})" (namely $\mu_{101}(rs_6)>\gamma$) THEN $A^{(11)}$ belongs to "cell 5".

Rule 7: IF $A^{(2)}$ belongs to "17:00:00(t3)" (namely $\mu_{23}(t)>\gamma$) AND $A^{(3)}$ belongs to "middle speed (V_2)" (namely $\mu_{32}(v)>\gamma$) AND $A^{(8)}$ belongs to "strong(I_{82})" (namely $\mu_{82}(rs_4)>\gamma$) THEN $A^{(11)}$ belongs to "cell 4".

Rule 8: IF $A^{(2)}$ belongs to "17:00:00(t3)" (namely $\mu_{23}(t)>\gamma$) AND $A^{(3)}$ belongs to "middle speed (V_2)" (namely $\mu_{32}(v)>\gamma$) AND $A^{(8)}$ belongs to "weak(I_{81})" (namely $\mu_{81}(rs_4)>\gamma$) THEN $A^{(11)}$ belongs to "cell 5".

Rule 9: IF $A^{(3)}$ belongs to "low speed (V_1)" (namely $\mu_{31}(v)>\gamma$) AND $A^{(9)}$ belongs to "strong(I_{92})" (namely $\mu_{92}(rs_5)>\gamma$) THEN $A^{(11)}$ belongs to "cell 5".

Rule 10: IF $A^{(3)}$ belongs to low speed (V_1) (namely $\mu_{31}(v)>\gamma$) AND $A^{(9)}$ belongs to "weak(I_{91})" (namely $\mu_{91}(rs_5)>\gamma$) THEN $A^{(11)}$ belongs to "cell 6".

3.2.2. Mobility prediction procedure: It is described as follows:

Step1. Get the values of $A^{(1)}$, $A^{(2)}$, $A^{(3)}$, $A^{(4)}$, $A^{(5)}$, $A^{(6)}$, $A^{(7)}$, $A^{(8)}$, $A^{(9)}$ and $A^{(10)}$ for the MU, and then make them to be fuzzy;

Step2. Based on the fuzzy decision tree, look up one or multiple fuzzy decision rules of which condition fuzzy sets are matching with the MU's movement situation. If no such rule found, the prediction has failed and the procedure ends, otherwise goto Step 3;

Step3. If one or multiple fuzzy decision rules predict that the MU's target cell belongs to the same one, regard it as the target one; if multiple fuzzy decision rules predict different MU's target cells, regard all of them as the target ones, the procedure ends.

3.3 Fuzzy decision tree maintenance

Sometimes due to the changes of the roads or buildings and even the movements of the base stations (for example mobile communication vehicles), the covering scopes of the cells may be changed, leading to the prediction accuracy based on the existing fuzzy decision tree decreased. Thus, it is necessary to maintain the fuzzy decision tree in time.

Definition 6: for one fuzzy decision rule, the ratio of the times of its right predictions among all of its prediction times is called its prediction-hitting rate (PHR).

Because each leaf node in fuzzy decision tree corresponds to one fuzzy decision rule, it is also called PHR of leaf node, denoted by p_r.

Definition 7: the average PHR of all leaf nodes in fuzzy decision tree is called the PHR of the tree, denoted by p_t.

Definition 8: the PHR variance of all leaf nodes in fuzzy decision tree is called the prediction variance of the tree, denoted by σ_t.

Three tree maintenance operations are described as follows:

Reconstruction: rebuild the fuzzy decision tree based on the current instance set, and thus regenerate the fuzzy decision rules.

Pruning: prune the leaf nodes (corresponding to the fuzzy rules) and their associated branches and nodes.

Divarication: change the leaf node to the child one, build a fuzzy decision sub-tree based on the initial fuzzy decision tree construction algorithm and then graft it to the tree.

Suppose the threshold of p_r to be P_r, the threshold of p_t to be P_t, and the threshold of σ_t to be Δ_t, the following maintenance procedure is performed:

①If $p_t < P_t$, reconstruct the fuzzy decision tree；

② If $p_t \ge P_t$ and $\sigma_t > \Delta_t$, traverse each leaf node of the tree. If the prediction times of a leaf node is zero, prune it; if not zero and $p_r < P_r$, divaricate the tree; otherwise, do nothing.

4 Simulated research and performance evaluation

Simulated research and performance evaluation have been done under SAS8.2 [14]. Fig.9 is the illustration of partial layout of one certain campus, and cells 0-6 are seven cells within it. In order to evaluate the proposed mechanism, the actual handoff situations from cell 0 to cell 1-6 have been observed, and about 6000 observation records have been got. Based on the observed time order, the former 70% records consist of the instance set to produce the initial fuzzy decision tree, and the latter 30% records consist of the test set to evaluate the proposed mechanism.

As shown in table 1, with the decrease of γ (see 3.1.4), both the depth of the fuzzy decision tree and the number of the leaf nodes (fuzzy rules) increases, and thus the PHR improves, however, the multi-target-cell prediction ratio also increases, leading to the prediction overhead increased. Under the same condition, the multi-target-cell prediction ratio produced by the method in [7] is about 26.3% while it is no more than 5.2% produced by the one proposed in this paper, hence the overhead of the proposed mechanism in this paper is much lower.

Set $\gamma = 0.1$ and compare the proposed mechanism in this paper with that in [7] under different movement velocity. The results are shown in Fig.10. When the MU's movement velocity is lower, the PHR of the proposed mechanism in this paper is higher than that in [7]; however, when the MU's movement velocity is higher, the PHR produced by the method in [7] is higher.

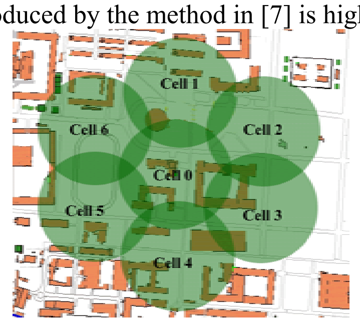

Fig.9. **Partial layout of one certain campus**

Table 1 **PHR under different values of** γ

γ	Number of fuzzy rule	Depth of fuzzy decision tree	Multi-target-cell prediction ratio(%)	PHR(%)
0.5	1	1	1.2	11.6
0.4	2	2	1.2	30.0
0.3	4	3	1.4	62.2
0.25	5	4	1.7	86.8
0.2	7	5	1.9	95.3
0.15	10	6	2.5	98.8
0.1	14	7	2.9	99.5
0.05	20	8	3.5	99.5
0.02	38	9	5.2	99.5

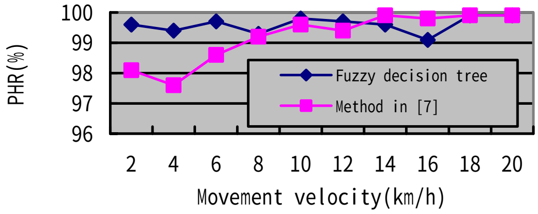

Fig.10. **Comparison of PHR under different velocity**

5 Conclusions

In this paper, a fuzzy decision tree based mobility prediction mechanism in mobile Internet is proposed. Simulation results have shown that its prediction-hitting rate is relatively higher with relatively lower overhead, and thus it is both feasible and effective.

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