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Exploiting mobility patterns for inter-technology handover in mobile environments

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ABSTRACT

Mobile terminals with multi-radio devices have become increasingly prevalent. This makes it possible for Internet applications to be supported by heterogeneous wireless networks while the terminal is on the move. As the user is constantly moving, it is highly desirable that the terminal connects to the best network and retains high performance of network connections. Handovers can be made within the same type of network (horizontal handover) or different types of networks (vertical handover). This paper focuses on *link-layer inter-technology vertical handovers*. Vertical handovers present several great challenges, such as user mobility randomness, high handover overhead and optimality requirement. Existing work often focuses only on the current network condition when making handover decisions, ignoring future performance of the terminal. As a result, a handover decision good for the current moment may soon become poor when the user moves to another place. This paper is motivated by the observation that users in a given mobile environment, such as university or enterprise campus, exhibit clear mobility patterns. We propose an approach for making handover decisions, which explicitly exploits user mobility patterns. This approach can produce high-performance handover decisions in the long run. Employing a comprehensive framework for preference customization, the approach supports user customization caring for different user preferences. Extensive real trace driven simulations and comparative study show our algorithm is better than the conventional vertical handover algorithms.

1. Introduction

Recent years have witnessed the boom of different wireless technologies including WiFi, WiMAX, 3G and LTE [4]. It has become increasingly prevalent for mobile terminals, such as notebook, PDA and smart phones, which are equipped with multi-radio devices. As a user is moving in an environment with heterogeneous wireless access technologies, the terminal can connect to different network access points [14]. The IEEE 802.21 working group has been working towards the standardization of Media Independent Handover (MIH) [5], i.e., towards seamless handover between IEEE 802 and non-IEEE 802 (e.g., 3GPP, 3GPP2) access technologies. It will become possible for users to roam among different wireless networks by integrating various wireless access networks with the help of network-layer (IP) mobility management architectures [12], such as Mobile IP [2], Mobile IPv6 [3] and Proxy Mobile IPv6 [1]. By actively switching among different wireless networks, the user may be able to experience better network connection performance [6].

Traditionally, a horizontal handover is made when there is only one type of wireless network, with the user changing from one network attachment point to another in the same network. When there are over two types of wireless networks, not only horizontal handover but also vertical handover is possible. A vertical handover is made when the mobile terminal migrates across different wireless networks. It usually involves three major phases: i.e., system discovery, vertical handover decision and vertical handover execution [15]. In the system discovery phase, the mobile terminal periodically senses its current network condition. The network condition may include many dynamic parameters, such as network feasibility, available bandwidth, delay, jitter, and coverage. In a wireless environment, the network condition of a mobile terminal is largely determined by the location of the user. In the vertical handover decision phase, a base station or access point selection should be made with the objective of maximizing the connection performance of the user. In the last phase, the vertical handover decision is executed and the terminal connects to the selected base station. A typical execution process includes authentication, association, transfer of the context information, and update of wired network routers. This process may introduce handover cost, such as delay and interruption to ongoing sessions.

This paper focuses on link-layer inter-technology handovers. More specifically, we study vertical handover decisions in a

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heterogeneous mobile environment in which different types of wireless networks may exist. Network-layer (IP) handover is beyond the scope of the paper. Compared with typical horizontal handover, vertical handover in a heterogeneous of multiple wireless networks is more complicated. First, network indicators of different types of networks, such as Received Signal Strength (RSS) may not be comparable. Second, inter-technology handovers may introduce performance degradation to mobile terminals, and therefore vertical handover overhead should be considered when making handover decisions.

A number of methods [7,16,18,23,28] have been proposed for vertical handover in wireless networks. They model the handover as a Multiple Attribute Decision Making (MADM) problem. The Simple Additive Weighting (SAW) ranks candidate networks with weighted sum of all attribute values. The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) chooses the network that is the closest to the ideal solution and farthest from the worst case. The Analytic Hierarchy Process (AHP) constructs a decision hierarchy, and compares each factor to all the other factors and calculates the sum of weights obtained from each levels of the hierarchy; The Grey Relational Analysis (GRA) ranks all the candidate networks and selects the one with the highest ranking. In [19,20], the numerical experiments show that the typical MADM provides almost similar performance, depending on the weights assignment of the parameters.

These existing methods tend to connect to a base station with highest network performance indicators, and thus they are greedy in essence. Moreover, they make handover decision solely based on the current condition, ignoring future user performance. As a result, the handover decision is usually suboptimal. In general, a higher randomness degree of user mobility would result in worse performance [10]. In practice, a user is moving constantly and user mobility possesses a great degree of randomness. The overhead of vertical handover should be explicitly considered, which may degrade user experience. It is highly desirable that handovers should be made for maximizing the user experience in the long run.

We have the important observation that users in some environments, such as university or enterprise campus, may exhibit strong mobility patterns. We demonstrate the existence of mobility regularity with user mobility by mining a large dataset of user traces extracted from WiFi log in Dartmouth College [11], as shown in Fig. 1.

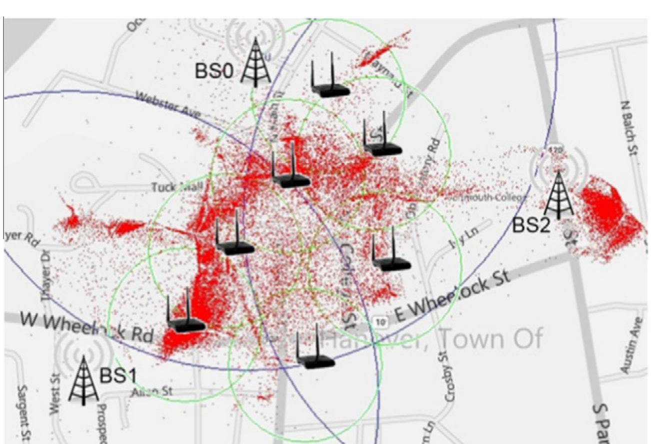

Fig. 1. User distribution in the Dartmouth campus, where a red dot represents a user connected to a WiFi access point. The distribution of users is drawn according to the trace data from the Dartmouth campus. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Motivated by this observation, this paper proposes an approach for making handover decisions, which explicitly exploits user mobility patterns in mobile environments. The handover process is formulated as a Markov decision process, and a policy iteration algorithm is developed to compute the optimal policy of handovers. With this computed policy, the expected user utility in the long run is maximized. Since a vertical handover has to consider a variety of parameters, we employ AHP for determining the relative importance of different parameters. This produces a customized solution, allowing different users to define user specific criteria. We evaluate the performance of our approach with trace-driven simulations, and compare it with several alternative algorithms. It is shown that our algorithm considerably outperforms the other algorithms.

In this paper we have made the following technical contributions.

- By mining a large dataset of real user traces, we reveal that there is strong regularity with user mobility in a mobile environment.
- We leverage the framework of Markov decision process to formulate the handover process in a mobile environment with different wireless technologies. Our algorithm can achieve high user performance in the long run.
- Extensive trace-driven simulation have been conducted and conclusive results show that our algorithm is better than other existing algorithms.

The remainder of the paper is organized as follows. In Section 2, we discuss the related work. The system model and the problem statement are introduced in Section 3. In Section 4, we reveal the strong regularity of user mobility by analyzing the dataset of user traces. Section 5 describes our proposed solution in detail. In Section 6, implementation details are presented. In Section 7, we present trace-driven simulations and show the performance of our solution compared with other algorithms. Finally, we conclude this paper in Section 8.

2. Related work

Handover issues have been extensively studied, and handover approaches can be generally divided into two categories: horizontal handover and vertical handover. Horizontal handover, e.g., [17], occurs in homogenous wireless networks and vertical handover occurs in heterogeneous wireless networks. In this section, we review existing approaches for vertical handover.

A number of algorithms [7,13,18,25,28] have been proposed for vertical handover. Guo et al. [7] propose an adaptive multi-criteria vertical handover decision algorithm, which uses a fuzzy interface system and a modified Elman neural network. Simulations have been performed and results show that the handover decision algorithm achieves better performance in guaranteeing QoS of the after-handover communication. Wu [23] applies fuzzy logic in heterogeneous wireless networks handover decisions and introduces the fuzzy normalization concept to make parameters for heterogeneous wireless network normalization. Through simulations it is demonstrated that better network load can be achieved.

A network selection mechanism is proposed in [18], where AHP and GRA are integrated to make an optimal selection based on time-varying QoS information through cross-layer signaling. The AHP trends to be the most popular method for vertical handover decision based on multiple attributes. Then GRA is applied to rank them and the network with highest score is finally selected. These algorithms tend to make greedy decisions based on a value evaluation of current network conditions.

In [25], an integrated network of WiFi and WiMAX is considered. It studies the problem of energy-efficient handovers and proposes a handover scheme with geographic mobility awareness. In [28], new handover criteria are introduced and a handover decision strategy is proposed. The handover process is formulated as a fuzzy multiple attribute decision making problem and fuzzy logic is used to deal with inaccurate information of criteria and user preference.

In [19,21,27], the vertical handover decision problem is formulated as a decision process and algorithms are devised to derive the conditions under which a handover should be made. However, they simply make the assumption that the mobile terminal can be modeled as a Markov chain. In addition, little effort has been done to evaluate their algorithms in a realistic environment.

In [26], a framework for performance comparison of handover algorithms is proposed. There are several factors that should be considered for handover decision making such as application QoS requirements and handover delay. Two different algorithms were compared, which shows the tradeoff between achieving high resource utilization and satisfying user QoS expectations.

In summary, some of existing algorithms make greedy decisions with only current network conditions or make little effort in exploring user mobility and performance evaluation is conducted with artificial configurations. This paper tries to exploit user mobility patterns. An optimal handover strategy is computed, which explicitly takes the advantage of mobility regularity. In addition, the performance of the proposed approach is evaluated in a realistic environment with a large dataset of user traces in a campus setting.

In our approach we need to extract mobility patterns from user historical traces. In [11], a methodology is proposed for extracting user traces from the WiFi AP log data. They collected the log data that record all association events of mobile terminals with APs over several years. Three algorithms were proposed to estimate user tracks and further a mobility model was built according to the user mobility. Experimental results show that the synthetic tracks match real tracks with a median relative error of 17%.

3. System model and problem statement

In this section we present the system model and formally describe the problem.

3.1. System model

In a mobile environment, there are multiple types of wireless networks, denoted as a set $N = \{0,1,\ldots,|N|-1\}$ and a set of base stations, denoted as $K = \{0,1,\ldots,|K|-1\}$. Each base station $k \in K$ belongs to a wireless network. The location of a base station i is denoted by p_i and its wireless coverage radius by r_i. The coverage areas of the base stations may overlap, and this suggests that when a user in the overlapping area a handover decision can be made. In our simulations, there're three WiMAX base stations and seven WiFi access points can be deployed and their coverage denoted by the overlapped circles. Without loss of generality, this paper considers a mobile environment in which there are two different types of wireless network, e.g., WiFi and WiMAX [24].

A mobile terminal m is equipped with multiple radio interfaces. For simplicity, this paper assumes that the number of radio interfaces equals the number of the types of wireless networks (i.e., 2). Furthermore, we assume that the mobile terminal is authorized to roam in the mobile environment. Specifically when residing in an overlapping area, the mobile terminal can choose one out of the available base stations to connect. The current base station that m is connected to at time t is denoted by $\varpi_m(t) \in K$.

The mobile terminal is moving constantly over the given mobile environment. The position of terminal m at time t is denoted by $p_m(t)$. Each terminal periodically senses the SNR of all base stations, $\vartheta_m(k)$, $\forall k \in K$. Once the terminal senses the channel condition, it will bring an immediate cost ς_{im} denoting the energy consumption and the interference on the session caused by sensing operation. The period for channel sensing is denoted by τ. Note that this period controls the tradeoff between sensing cost and handover sensitivity. Channel sensing is a costly operation as it consumes considerable power when the radio interface scans the radio channel. In addition, channel sensing may interfere the ongoing transmission sessions. At the same time, if the period is too long, the terminal becomes insensitive to change of network conditions. In practice, this can be determined based on the user requirements on sensing cost and handover sensitivity.

At the end of each period, each mobile terminal, m, decides to which it connects or just remains connected to the current base station $\varpi_m(t)$. When a handover from the current base station $\varpi_m(t)$ to another base station $\delta_m(t) \in K$ is made, there is an associated cost, $\varsigma_{as}(\varpi_m(t), \delta_m(t))$. This cost accounts for degrade in user perceived performance, e.g., latency introduced or ongoing TCP connection disruption. There is no associated cost when the terminal decides to remain with the current base station. The entire cost of one handover operation $\varsigma(\varpi_m(t), \delta_m(t))$ is the sum of the immediate cost and the associated cost,

$$\varsigma(\varpi_m(t), \delta_m(t)) = \varsigma_{im} + \varsigma_{as}(\varpi_m(t), \delta_m(t)). \tag{1}$$

In the following period, the performance gain of terminal m obtained by switching from $\varpi(m)$ to the new base station is dependent on the actual motion trajectory of m in the next time period τ, $\upsilon_m(t, t+\tau)$. This is because under a deterministic wireless network setting, the motion trajectory of the terminal primarily determines the dynamic network condition that it will experience in the period. Let $\varphi_m(t, t+\tau)$ denote this performance gain and it is a function of $\upsilon_m(t, t+\tau)$. Note that different terminals may have different forms of the function, depending on user preferences.

3.2. Problem description

The overall objective is to optimize the terminal's perceived network performance for a sufficiently long time from the initial time 0 to an ending time instant T. Then, we want to maximize the user perceived performance over the whole duration from 0 to T. Let t_i, $0 \leqslant i < q$, $q = T/\tau$, denote the decision time, namely, a time instant when the ith handover decision is made.

Then the overall objective is to maximize the user total utility U_m defined as the total performance gain minus the total cost.

$$U_m = \alpha \sum_{i=0}^{q-1} \varphi_m(t_i, t_{i+1}) - (1-\alpha) \sum_{i=0}^{q-1} \varsigma(\varpi_m(t_i), \delta_m(t_i)), \tag{2}$$

where $\alpha \in [0,1]$ is the weight given to the expected performance gain, which varies with user preferences and application requirements, etc.

4. Mobility regularity analysis

In this section, we show that there exists strong regularity with user mobility. The quantitative analysis is carried out by mining a large dataset of user traces extracted from WiFi log in Dartmouth College's 269-acre campus, which contains more than 6200 campus users between 2001 and 2003. The trace of each user is formed by a series of locations with timestamps. In our analysis, more than 5,000,000 traces are employed from the dataset.

For simplification, we divide the whole campus space into Q small grids. Hence, the whole space can be denoted by

$$Z = \{z_0, z_1, \ldots, z_{Q-1} | z_i \cap z_j = \varnothing,\ i \neq j\}. \tag{3}$$

The user location at a given time thus can be considered as a random variable which takes a value from the grid space Z. Let X_i denote the random variable for user i. We reveal the mobility regularity by computing the marginal and the conditional entropies of X_i given the previous Y states. The marginal entropy measures the uncertainty of a user's location in the whole space, while the conditional entropy reveals the uncertainty of the user's next location when the previous Y states are given.

Suppose we observe the user movement with an interval of τ, and we have a total of L observations. The state sequence of the user location can be denoted by a vector $\overrightarrow{X}_i = \langle x_0, x_1, \ldots, x_{L-1}\rangle$, where $x_j \in Z$, $0 \leqslant j \leqslant L-1$ is the positional state of user i at the jth observation. We use ℓ_j to denote the appearance frequency of x_j in the vector $\overrightarrow{X}_i$, $0 \leqslant j \leqslant L-1$. Thus, the probability of positional state x_j that user i locate in is ℓ_j/L. Then the marginal entropy of X_i is

$$H(X_i) = \sum_{j=0}^{L-1} (\ell_j/L) \times \log_2 \frac{1}{\ell_j/L}. \tag{4}$$

Then we compute the conditional entropy of X_i given its previous positional state X_i^1 using

$$H(X_i|X_i^1) = H(X_i, X_i^1) - H(X_i). \tag{5}$$

To calculate $H(X_i, X_i^1)$, we transform $\overrightarrow{X}_i$ into 2-tuple format, $\overrightarrow{X}_i^1 = \langle (x_0, x_1), (x_1, x_2), \ldots, (x_{L-2}, x_{L-1})\rangle$. Similarly, we denote the appearance frequency of (x_{j-1}, x_j) by $\ell_{j-1,j}$, $1 \leqslant j \leqslant L-1$. Hence, the joint entropy can be computed by

$$H(X_i^1, X_i) = \sum_{j=1}^{L-1} (\ell_{j-1,j}/(L-1)) \times \log_2 \frac{1}{\ell_{j-1,j}/(L-1)}. \tag{6}$$

Furthermore, in a similar way, we compute the condition entropy of X_i given its previous two state $X_i^1,\ X_i^2$,

$$H(X_i|X_i^1, X_i^2) = H(X_i, X_i^1, X_i^2) - H(X_i). \tag{7}$$

The cumulative distribution functions (CDFs) of marginal and conditional entropies are shown in Fig. 2. The grid size is $10\ \text{m} \times 10\ \text{m}$ and the observation length $L = 10{,}000$. Since many user traces are shorter than this observation length, we combined several different user traces to form virtual user traces. Note that in the virtual trace the marginal transition between two states from different origin user traces is ignored and thus the virtual user traces comply with reality. In this case, we formed 557 virtual user traces from the original user traces. As we can see from Fig. 2, the conditional entropy is considerably lower than the marginal entropy. This implies that the uncertainty of user location decreases when the previous locations are known. In addition, when given the previous two states, the conditional entropy decreases by only a small amount, and when more previous states are given the decrease in entropy becomes marginal. This strongly suggests that the user mobility has a Markov property, that is, the next location is mainly determined by the current location.

We validate our hypothesis on Markovian user mobility by modeling user mobility with a Markov chain, and predict the next location given the current location. We split the traces into two halves. One half is used to establish the Markov chain model and the other is used to evaluate the prediction accuracy. We study prediction accuracy at different configurations of allowing the number of locations we can predict, denoted by n. If the predicted location is one of the predicted locations, we count it as a hit. Fig. 3 shows the CDF of prediction accuracy for different$n$. From the figure, we can see that the precision is considerably high, which validates our hypothesis on Markovian user mobility.

5. Mobility patterns aware handover

Handover decisions should help to maximize the user experience. The previous section has revealed that user mobility exhibits strong regularity characterized by a Markov chain. Thus, handover decisions should take into account the user mobility regularity.

To solve the handover problem with the objective as stated in (2), we formulate the handover process as a Markov decision process and then derive the policy for making handover decisions.

5.1. MDP formulation

In this paper, the handover process of a mobile terminal m is modeled as MDP which is characterized by a 4-tuple: (S,A,P,R), where S is the set of all the user states, A is the set of all handover actions, $P_a(s,s') = \Pr(s_{i+1} = s'|s_i = s, \delta_i = a)$ is the probability that action a in state s at time t_i leads to state s' at time t_{i+1}, $R_a(s,s')$ is the reward after taking the action a at state s and leading to a new state s'.

At time t_i, the terminal senses the SNR of each base station $\vartheta_i(k)$, $\forall k \in K$. The SNR values of all base stations are contained in vector $\overrightarrow{\vartheta_i}$,

$$\overrightarrow{\vartheta_i} = \langle \vartheta_i(0), \vartheta_i(1), \ldots, \vartheta_i(|K|-1)\rangle. \tag{8}$$

The SNR value can be divided into different regions. SNR within one region usually indicates relatively stable network performance (e.g., data transmission rate) [8,22]. Thus, the state space of the SNR vector would be limited. Let Θ denote the set of all possible SNR states of the terminal. The state of the terminal $s \in S$ is defined jointly by $\overrightarrow{\vartheta_i}$ and its current base station ϖ_i,

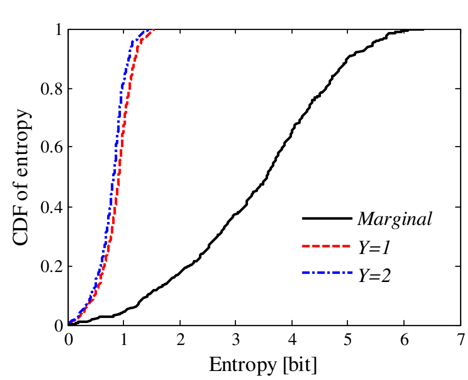

Fig. 2. The CDFs of marginal entropy and conditional entropies of a user positional state.

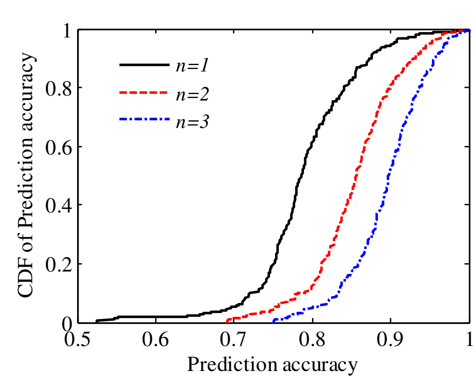

Fig. 3. The CDFs of prediction accuracy, where the number of tolerable locations is: $n = 1$–3.

$$s_i = (\overrightarrow{\vartheta_i}, \varpi_i). \tag{9}$$

An action $a \in A$ denotes the specific base station that the terminal decides to connect, and then $a \in K$. Obviously, $a_i = \varpi_i$ when the terminal decides to remain connected to the current base station.

In order to derive P, we compute $P_a(s,s')$ for each $a \in A$, each $s \in S$ and $s' \in S$, as follows

$$P_a(s,s') = \Pr(s_{i+1}|s_i,a_i) = \begin{cases} \Pr(\overrightarrow{\vartheta_{i+1}}|\overrightarrow{\vartheta_i}), & \text{if } \varpi_{i+1} = a_i \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

This equation shows that the uncertainty of the next possible state s_{i+1} is only related with the first component $\overrightarrow{\vartheta_{i+1}}$ and ϖ_{i+1} is determined by the action taken in the end of last period a_i. Thus we need $\Pr(\overrightarrow{\vartheta_{i+1}}|\overrightarrow{\vartheta_i})$ for computing P.

Given the terminal, we can derive $\Pr(\overrightarrow{\vartheta_{i+1}}|\overrightarrow{\vartheta_i})$ by investigating a sufficiently long history of network conditions of this terminal. Let the historical network condition sequence of the terminal over the a past duration L be denoted by $\langle \overrightarrow{\vartheta_0}, \overrightarrow{\vartheta_1}, \ldots, \overrightarrow{\vartheta_{L-1}} \rangle$. We use o_{ϑ} to denote the appearance times of the vector variable $\vec{\vartheta}$ in the sequence and use $o_{\vartheta,\vartheta'}$ to denote the times of transition from $\vec{\vartheta}$ to $\overrightarrow{\vartheta'}$. Thus the transition probability $\Pr(\overrightarrow{\vartheta'}|\vec{\vartheta})$ is

$$\Pr(\overrightarrow{\vartheta'}|\vec{\vartheta}) = \frac{\Pr(\vec{\vartheta}, \overrightarrow{\vartheta'})}{\Pr(\vec{\vartheta})} = \frac{o_{\vartheta,\vartheta'}/(L-1)}{o_{\vartheta}/(L-1)} = \frac{o_{\vartheta,\vartheta'}}{o_{\vartheta}}. \tag{11}$$

It is worth noting that, the Markovian user mobility regularity indicates that the historical trace of network conditions of the terminal also has the Markovian property. As discussed in Section 3.1, the location of the terminal primarily determines the network condition that it experiences under deterministic wireless network setting. Thus, the regularity of user mobility actually reveals the regularity of network conditions. In this way, the MDP formulation explicitly exploits the regularity property.

It is desirable for a mobile terminal to obtain high performance of network connection while minimizing the overhead caused by handovers. We define the reward $R_a(s,s')$ as a utility function by jointly considering expected performance gain $f(a,s,s')$ and overhead $g(a,s)$.

$$R_a(s,s') = \alpha f(a,s,s') - (1-\alpha) g(a,s), \tag{12}$$

where $\alpha \in [0,1]$ is a controlling weight allowing different users to set different preferences on the reward, $f(a,s,s')$ and $g(a,s)$ are normalized between [0,1] with their maximum and minimum values. Therefore, the range of $R_a(s,s')$ is $-1 \leqslant R_a(s,s') \leqslant 1$.

In (12), the expected performance gain function $f(a,s,s')$ is the average of the performance gains at state s and s',

$$f(a,s,s') = (h(a,s) + h(a,s'))/2, \tag{13}$$

where $h(a,s)$ is the normalized immediate performance gain function depended only on action a and current state s. The immediate performance gain should consider multiple factors, such as bandwidth, jitter, coverage and delay. This function is important and will shortly be discussed in the next subsection. The handover overhead function characterizes the overhead introduced when a handover is made, e.g., additional latency and power consumption. If the terminal decides to remain with the current base station, there is no handover overhead except the sensing channel cost as introduced previously in section 3.

5.2. Performance gain function

The performance gain function is important for making vertical handover decisions. A number of important factors should be taken into account, such as bandwidth, jitter, network delay, and coverage. This function may be different for different users as they may have varying preferences over the performance metrics. In our paper we employ the Analytic Hierarchy Process (AHP) to construct the performance gain function. AHP provides a comprehensive and rational framework for multiple criteria decision-making.

In general, AHP has four steps. Firstly, AHP constructs a hierarchy for modeling a decision process. The hierarchy of independent impact elements is shown in Fig. 4. The root of the hierarchy is the overall objective, that is, the performance gain. Four major factors are located on the second level and the bottom nodes are the available k base stations, $k \leqslant |K|$.

Next, all k available base stations on the third level are compared in pair in terms of each factor on the second level. Each comparison result is the ratio of the numerical measure of each factor. For instance, the bandwidth comparison matrix M_b is of dimension $k \times k$, whose value is $(M_b)_{ij} = b_i/b_j$ where b_i is the available bandwidth of the ith base station. The four major factors are also compared with each other, and each comparison result is a value from 1 to 9 meaning the degree of relative importance, according to user' preference. The comparison matrix of the four elements is denoted by M_e of dimension 4×4.

At the third step, the normalized eigenvector of the resulting matrix is computed, which indicates the weights of elements. The computed $k \times 1$ weight vectors for k BSs in terms of bandwidth, jitter, delay and coverage are denoted by W_b, W_j, W_d and W_c respectively and the 4×1 weight vector for the four factors is denoted by W_e.

Finally, it aggregates the weights of different elements on all the levels and eventually computes the performance gain as follows,

$$h(a,s) = W^{(a)} = (W_e^T \cdot [W_b, W_j, W_d, W_c]^T)^{(a)}. \tag{14}$$

where $W^{(a)}$ means the ath column of the $1 \times k$ dimension matrix. Note that since all the weight vectors in (14) are normalized, thus $h(a,s) \in [0,1]$.

5.3. Computing optimal policy

In order to make optimal handover decision in the long run, we derive the optimal handover policy ρ that determines the action a for each state s, i.e., a mapping function $\rho : s \mapsto a$. The policy is so selected that it maximizes the expected discounted cumulative rewards with discount factor $\gamma \in [0,1]$,

$$\max_{\rho} \sum_{i=0}^{\infty} \gamma^i R_{\rho(s_i)}(s_i, s_{i+1}). \tag{15}$$

The discount factor γ indicates the discount degree of future reward. It enables the algorithm to evaluate the reward in the long term reliably.

We define $v^{\rho}(s)$ as the expected cumulative rewards starting from state s, which satisfies the following recursive property,

$$v^{\rho}(s) = E\left\{\sum_{j=0}^{\infty} \gamma^j r_j | s_0 = s; \rho\right\} = r(a,s) + \gamma \sum_{s'} P_a(s,s') v^{\rho}(s'), \tag{16}$$

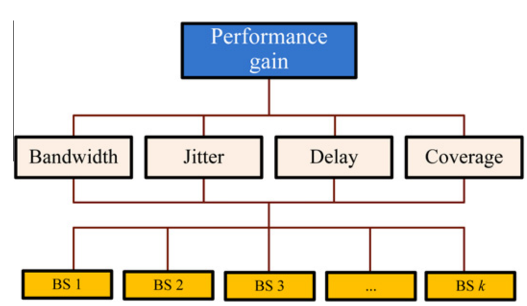

Fig. 4. AHP hierarchy model.

where $a = \rho(s)$, γ is typically close to 1 and $r(a,s)$ is the expected reward when action a is taken at state s,

$$r(a,s) = \sum_{s'} P_a(s,s')R_a(s,s'). \tag{17}$$

The optimal expected total rewards $v^*(s)$ and the optimal action $\rho^*(s)$ can be computed by

$$v^*(s) = \max_a \left[r(a,s) + \gamma \sum_{s'} P_a(s,s') v^{\rho}(s') \right], \tag{18}$$

$$\rho^*(s) = \arg\max_a \left[r(a,s) + \gamma \sum_{s'} P_a(s,s') v^{\rho}(s') \right]. \tag{19}$$

Based on (18) and (19), we design an algorithm based on the well-known policy iteration technique [9] for computing the optimal policy. The pseudo code of this algorithm is shown in Fig. 5.

It is worth noting that although this algorithm runs offline, the terminal can periodically sense the dynamic network condition state and makes the handover decision following the computed policy. Thus, the network selection decision process can be done in O(1), which reveals a much higher superiority of low latency and energy efficiency.

5.4. Discussion

By modeling the user mobility with a Markov chain, we extract the user's mobility regularity from the historical trace of the user. Exploiting this mobility regularity, we can take the next possible location of a user into account, which further primarily determines the next possible network condition. It is important that the current handover decision help to maximize the overall user performance in the long run.

Using the Markov chain model, a sampling time interval is implied. Within the time interval, the terminal retains connecting to the base station decided at the end of last time interval. So the time interval should be such set that the user location remains largely stable within a single time interval.

This decision interval should also be consistent for handover decision moments. It is intuitive that the sampling interval cannot be arbitrarily small as before the mobile terminal can make the handover decision it must scan all wireless channels to get the network conditions. This operation is actually costly in terms of time and power consumption.

In summary, the timer interval should strike a tradeoff between handover timeliness and scanning cost.

Input:
$X,\ K,\ P,\ R,\ \gamma$
Output: optimal policy ρ
Main process:
1: set $\nu^0(s) = 0$ for all states s, $k \leftarrow 0$
2: while (true)
3: compute $\nu^{k+1}(s)$ for each state s from

$$\nu^{k+1}(s) = \max_a \left[r(a,s) + \gamma \sum_{s'} P_a(s,s') \nu^k(s') \right]$$

4: record the optimal action for each state s in policy ρ

$$\rho(s) = \arg\max_a \left[r(a,s) + \gamma \sum_{s'} P_a(s,s') \nu^k(s') \right]$$

5: **if** $||\nu^{k+1}(s) - \nu^k(s)|| < \mathrm{v_{threshold}}$
6: **then return** ρ
7: **else** $k \leftarrow k+1$
8: end while

Fig. 5. Pseudo code of policy iteration algorithm.

6. Implementation

We have successfully implemented our handover approach. The architecture of the handover system is illustrated in Fig. 7. The system consists of four key components, i.e., *network monitor, trace logger, policy algorithm*, and *handover execution*.

The network monitor component periodically monitors the wireless signal quality from WiMAX and WiFi drivers. The sensed network condition is then logged by trace logger, and mapped to the current user state, together with the information of the current connected base station. With a considerably long historical movement trace and the metric parameters, the policy algorithm computes the optimal handover policy. The resultant policy is then feed into the handover execution module, which executes the handover decision. The handover execution is implemented by the system built-in *netsh* command line interface, which can be used to configure the routing table in the system.

We have implemented the handover system on a ThinkPad x120e laptop with AMD E350 CPU, 2G RAM running Windows 7. The laptop is equipped with two wireless NICs. The WiMAX NIC is an AX226 WiMAX USB Modem supplied by ZTE.

The developed handover system was tested in a real heterogeneous wireless environment, as illustrated in Fig. 6. In the Minhang campus of Shanghai Jiao Tong University in Shanghai, China, there are two types of wireless networks, i.e., WiFi and WiMAX which the campus users can enjoy. The WiMAX 802.16e network is backboned by the high-speed campus network. The three base stations jointly covers more than 70% of the 741-acre campus.

7. Performance evaluation

We conduct trace-driven simulations and compare our handover algorithm with several alternative handover algorithms.

7.1. Methodology and simulation setup

We have developed a discrete-event simulator for simulation study. Simulations are performed with real user traces in Dartmouth College's 269-acre campus [11]. There are two datasets of user traces with identical data structure. One is collected from 2001 to 2003 with more than 6200 users, and the other is collected

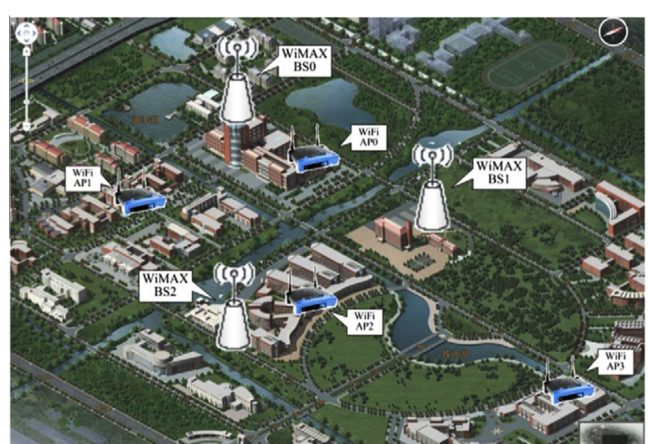

Fig. 6. The minhang campus of shanghai jiao tong university in which three Macro WiMAX base stations and many WiFi APs are deployed.

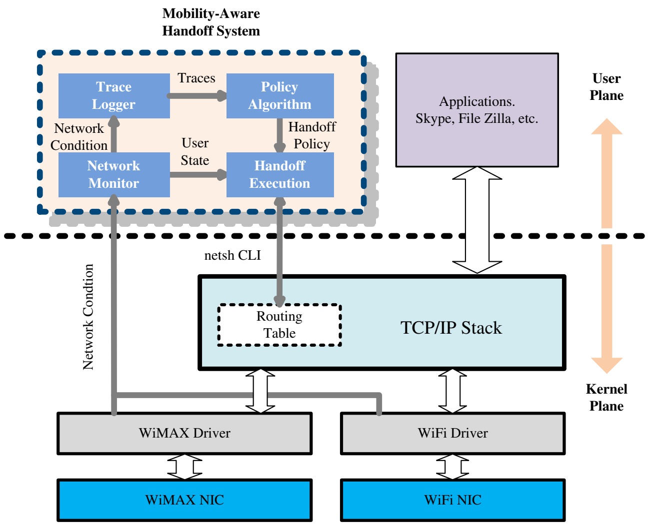

Fig. 7. Architecture of the handover system and the context with applications and the OS components.

from 2001 to 2004 with more than 13,000 users. In simulation, we use the larger one for optimal handover policy computation and the other for simulating the mobility of the users in simulations.

We consider two types of wireless networks, i.e., WiMAX and WiFi. Since the trace data only recorded the location information of users, and the wireless channel conditions were not recorded, we virtually deployed three WiMAX base stations and seven WiFi access points in the campus to simulate the mobile environment. The WiFi and WiMAX coverage radius are set to 150 m and 600 m, respectively. Their coverage ranges are overlapped so that users may have multiple choices when connecting to wireless networks. In simulation, the data rate is considered as an important metric of handover making. We employ the simplified models [8,22] to compute the available data rate of the two kinds of networks, which are extracted from measurements in real WiMAX and WiFi environments.

In performance evaluation, we use the *average user utility* as the performance metrics. According to (2) in Section 3, the average user utility u is defined as follows:

$$u = \frac{1}{q}\left(\alpha\sum_{i=0}^{q-1} h(\varpi_i, s_i) - (1-\alpha)\sum_{i=0}^{q-1} g(a_i, s_i)\right). \tag{20}$$

Without loss of generality, we assume the performance gain is a function of the data rate of a base station and the overhead is a function of the latency introduced by a handover in the simulations.

We compare our algorithm with two alternative algorithms described as follows.

Random Algorithm is an opportunistic handover decision algorithm, which randomly selects one available base station at each decision time.

Greedy Algorithm always selects the base station with the highest reward metric, denoted by

$$\rho^g(s) = \arg\max_a [\alpha h(a,s) - (1-\alpha) g(a,s)]. \tag{21}$$

As mentioned in section 2, the greedy algorithm is a representative of the state-of-the-art vertical handover algorithms, such as MADM [7,28], GRA [18], etc.

7.2. Comparative results

We study the average utility of all three algorithms. Fig. 8 shows the CDF of user utility that is computed over a trace. In this

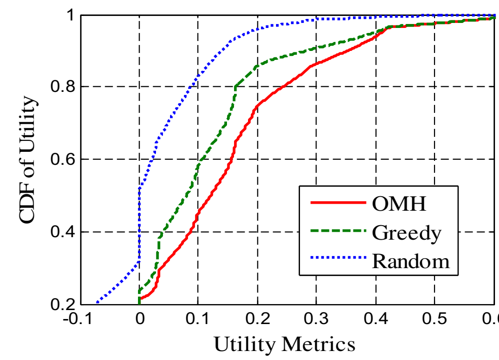

Fig. 8. CDF of user utility comparison among three algorithms ($\alpha = 0.7, \tau = 30$ s).

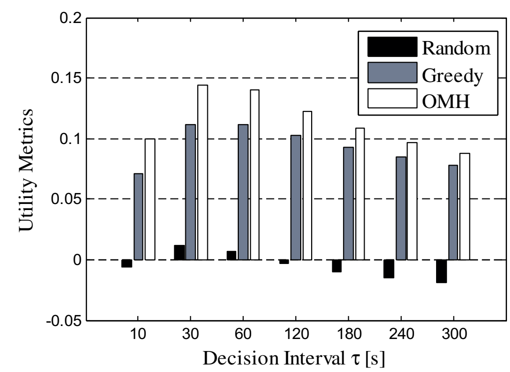

Fig. 9. Average utility comparison under different decision intervals ($\alpha = 0.7$).

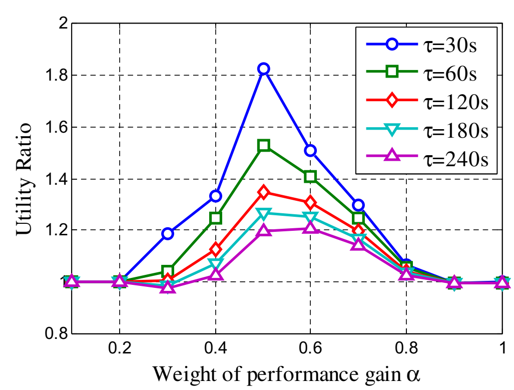

Fig. 10. Utility ratio of our proposed algorithm to the greedy algorithm under different performance weight α.

simulation, $\alpha = 0.7$, $\tau = 30$ s and $\gamma = 0.9$. We can see that our algorithm (denoted by OMH) outperforms both the random algorithm and the greedy algorithm. With our algorithm, over 57% traces have a utility of more than 0.1. With the greedy algorithm, only around 40% traces have a utility of more than 0.1. The random algorithm performs the worst, and about 80% of traces have a utility smaller than 0.1.

In Fig. 9, we further show the user utility averaged over all traces under different decision intervals. We can find that under all configurations of decision intervals, our algorithm is better than the two other algorithms. In addition, when the decision interval is 30 s, our algorithm performs the best among all configurations of decision interval. This suggests that the decision interval makes a good tradeoff when the decision interval is 30 s. As we can see in Fig. 9, when the interval is longer than 30 s, the utility decreases as the interval increases. This is because of the insensitivity to the change of network conditions. On the other hand, the utility decreases as the interval decreases when the interval is shorter than 30 s. It is mainly because frequent channel sensing introduces too much cost. This experimental result validates our discussion about the decision interval in Sections 3.1 and 5.4.

Finally, we compare the performance of the three algorithms with different relative weights of performance gain and handover overhead. We vary the weight from 0.1 to 1 and study the utility ratio of our algorithm to the greedy algorithm. In Fig. 10, the ratio under different configuration of relative weight and decision interval is shown. We can find that our algorithm steadily outperforms the greedy algorithm. When the weight is about 0.5, the ratio reaches the highest value, which indicates that our algorithm performs the best in contrast to the greedy algorithm when the weight is 0.5. When the decision interval is 30 s and the weight is 0.5, the utility ratio is as high as 1.8.

8. Conclusion

We have presented an approach for making vertical handover decisions in a heterogeneous mobile environment with wireless technologies, which explicitly exploits user mobility patterns. This approach determines the policy for making handover decisions, which can lead to high user performance in the long run. In addition, the algorithm employs the extensible AHP framework which allows users to customize their performance gains and therefore user preferences can be supported. With extensive simulations and comparative study, it has been shown that our mobility patterns aware handover approach considerably outperforms the conventional algorithms.

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