A Handoff Trigger Method using the Predictability of Received Signal Strength

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Abstract

In a mobile network, a timely and accurate handover decision is important to provide seamless services while efficiently using the system resources. In this paper, we propose a handover trigger method for fast handoff in a wireless LAN system. Through statistical analysis with the synthesized data, we verify that the autoregressive model of order 1 can be adopted to represent the received signal strength values in a short time interval. Using the predictability of the received signal strength, the proposed method initiates handover triggers in a timely manner. In addition, we show that simple compensation of the prediction error significantly decreases the rate of late handover triggers while maintaining a reasonable rate of false alarms.

Keywords: *Predictability of received signal strength, fast handover, timely handover trigger.*

1. Introduction

Handoff in a WLAN system can be classified into link layer handoff and inter-network handoff according to the scope of handoff [1]. Link layer handoff changes only wireless link between a mobile node (MN) and a serving access point (AP). On the contrary, inter-network handoff switches not only the wireless link but also a serving access router through which a MN accesses the Internet. Because a MN in a WLAN system can have only one active channel at any time, it takes a few hundreds of milliseconds to scan target APs when a MN needs to handoff [2]. This long delay causes high packet loss rate and long inter packet delay [3, 4]. Mobile IP (MIP) is a standard handoff management scheme for inter-network handoff. However, the standard MIP takes an order of a few seconds to finish handoff procedures. Moreover, MIP commences after link layer handoff finishes. This sequential handoff process is prohibitive for seamless service provisioning. To reduce the handoff delay, a fast mobile IP (FMIP) is specified in [5]. Basically, FMIP assumes a link layer trigger. The purpose of the L2 trigger is to notify a MN that a handoff is anticipated [6]. Owing to the L2 trigger, the required handoff procedures in a network layer can be completed before the current wireless connection is released. Using the concept, fast MIP over WLAN is introduced to reduce handoff delay of MIP [7, 8, 9]. They propose to start MIP procedures in parallel with link layer handoff using L2 trigger.

In the context of fast handoff, the purpose of L2 trigger is to inform a MN of anticipated handoff before target handoff delay so that the MN can finish required handoff procedures before it moves out of the areas of a serving AP. Accordingly, L2 trigger requires a prediction model to anticipate handoff. An inaccurate prediction model makes the resulting L2 trigger useless if the L2 trigger is generated later than desired target handoff delay (late L2 trigger). Moreover, prediction process inevitably introduces error. If the error is not controlled adequately, the rate of late L2 trigger can not be maintained at a desirable level. Therefore, a prediction model should be able to quantity the amount of error in the predicted value. In this paper, we propose and verify a prediction model to anticipate impending handoff. We also present how the prediction error can be controlled to timely generate L2 trigger. We note that the measured received signal strengths (RSSs) in a short time interval are highly correlated because the distance a MN can change in the time window is limited. Using the correlation structure, we propose an adaptive RSS predictor based on stationary time series process, which updates RSS data in a time window to predict *k*-step ahead RSSs at every RSS measurement interval. Using statistical analysis, we find that the autoregressive process of order 1 (AR(1)) can be used to represent RSS data in a time window. Simulation results show that even if 1-step ahead RSS is predictable via the AR(1) model in the sense that the prediction error is small with high confidence level, most of L2 triggers are generated later than given target handoff delay if the error is not controlled. To address this issue, we introduce a method to compensate the prediction error. Using ns-2 simulations, we showed that the compensation method improves the proposed L2 trigger scheme in terms of the late trigger rate and false alarm rate.

The rest of the paper is organized as follows. In Section 2, we identify the type of stationary time series model for a set of consecutive RSS values. In Section 3, we analyze the predictability of RSS values and propose a L2 trigger method. Then, we introduce a prediction error compensation method to initiate a L2 trigger timely and accurately. Using ns-2 simulations, we show the impact of RSS predictability on the L2 triggers in Section 4. Section 5 concludes the paper.

2. A Time Series Model for Received Signal Strength Values

The distance that a MN travels in a short time interval is limited. Therefore, it can be considered that the measured RSS values are highly correlated in a short time interval (called a time window). Taking an advantage of this correlation structure, an adaptive RSS prediction is possible with a stationary time series process. That is, the RSS values measured in a time window can help to predict the future RSS values, which is the key idea of this letter. In this section, we focus on identifying the stationary time series process that is most relevant to the RSS prediction.

2.1 Data Synthesis

The values of RSS may be affected by the mobility patterns of a MN and the characteristics of the radio propagation environment. Using ns-2 simulations, RSS is measured between a MN and an access point (AP) at every 0.5sec. In our simulations, a MN moves inside the cell coverage managed by an AP according to the random waypoint model [10, 11, 12]. Two parameters, the direction and the speed of the MN, are set to randomly vary in $[0, 2\pi)$ and [0, 10km/h], respectively.

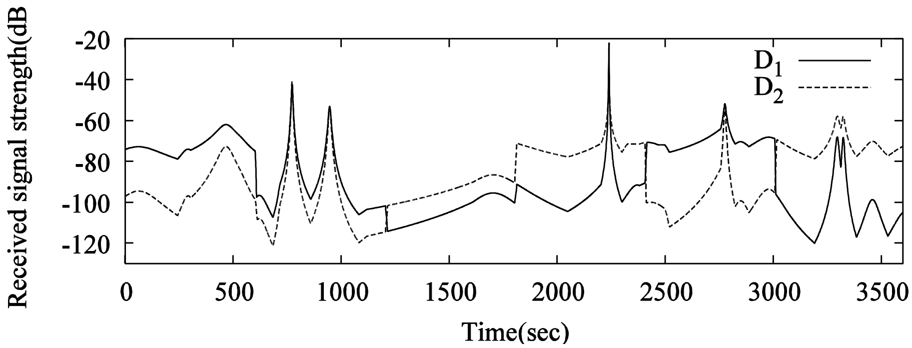

Figure 1. Synthesized RSS data set (D_1, D_2)

In order to emulate the practical heterogeneous cell environment in which the radio propagation characteristics may change from place to place even inside the same cell, we first measure RSS in three individual radio propagation environments differentiated by the path loss model [13]; free space (F), urban area (U), and obstructed area (O). Then, we randomly shuffle the order of the three radio propagation environments and concatenate the measured RSS accordingly. Figure 1 shows two synthesized RSS data sets. The first date set (D_1) is obtained when the radio propagation environment switches at every 10 minutes according to the following sequence; free space → urban area → obstructed area → urban area → free space. The second data set denoted by D_2 represents the scenario where a MN moves from one radio propagation environment to another at every 10 minutes according to the following sequence; urban area → obstructed area → urban area → free space → obstructed area.

2.2 Statistical Test Method

For the identification of an underlying stationary model, the autocorrelation function (ACF) and the partial autocorrelation function (PCF) are employed. Among the stationary time series processes, autoregressive process, moving average process, and autoregressive-moving average process are mostly used for a number of practical applications [14]. In case of the autoregressive process of order p (AR(p)), ACF tails off and PCF has a cutoff after lag-p. On the contrary, the ACF of the moving average process of order q (MA(q)) has a cufoff after lag-q while its PCF tails off. If both ACF and PCF tail off, it indicates the autoregressive-moving average process.

However, since we do not know the theoretical correlations, it is important to check how far estimated correlations from measured data may differ from the corresponding theoretical values. Especially, it is necessary to check whether theoretical ACF and PCF arve effectively zero after some specific lag. It was shown by Quenouille [15] that on the hypothesis that the process is AR(p), if n is the number of measured data used in model fitting, the standard error of the estimated PCF of AR(p) process at lag j ($\sigma[\widehat{\emptyset}_{jj}]$) is approximated by

$$\sigma[\widehat{\emptyset}_{jj}] \cong \frac{1}{\sqrt{n}}, (\mathrm{j} > \mathrm{p}). \tag{1}$$

Therefore, the estimated PCF can be considered as zero if the estimated PCF from a data set is within $\pm\sigma[\widehat{\emptyset}_{jj}]$.

In order to identify a stationary process for RSS in a time window, the synthesized RSS data sets (D_1 and D_2) is divided into time windows of 10 seconds. From all the windows, five time windows are taken to represent the following situations. During the time window S_1, the RSS values are increasing gently while the RSS values in a time window S_2 are declining rapidly. The RSS values in the time window S_3 ascent rapidly while they decline gently during the time window S_4. The time window S_5 represents the scenario where the radio propagation environment changes from a free space (F) to an urban area (U).

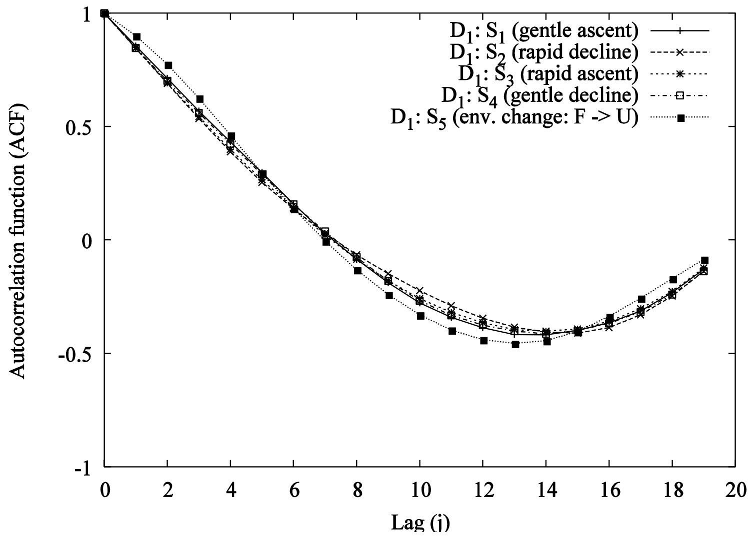

Figure 2. ACFs of RSS data in different time windows

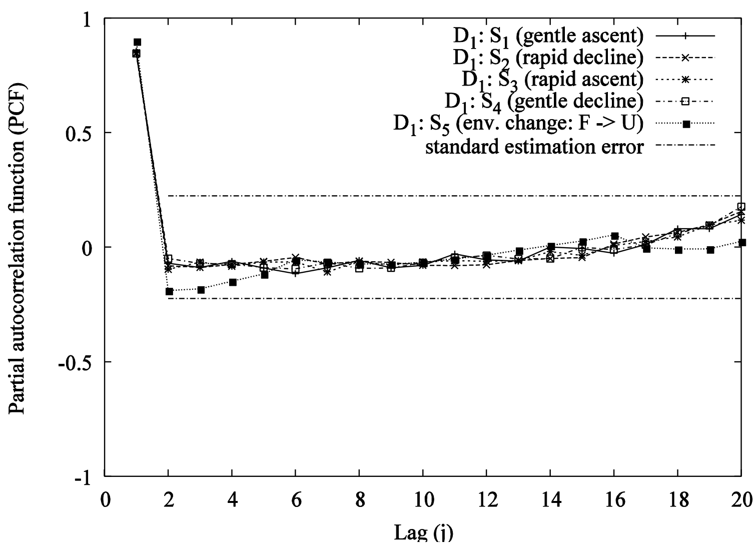

Figure 3.PCFs of RSS data in different time windows

For $S_1 - S_5$, ACFs are shown in Figure 2 and PCFs are shown in Figure 3. The dashed lines in Figure 3 are $\pm\sigma[\hat{\phi}_{jj}]$ about zero. These lines are drawn to assess the estimated partial autocorrelation functions. As can be seen in these figures, all the ACFs tail off. The PCFs can be considered to cut off after lag-1 because the PCFs after lag-1 are located between the two dashed lines representing $\pm\sigma[\widehat{\emptyset}_{jj}]$. These results suggest that the measured RSS values in a time window can be represented by the AR(1) process.

3. Predictability of RSS Values and Handover Trigger

3.1 RSS Value Predictor

Let T be the RSS measurement interval, and denote z_t, z_{t-1}, z_{t-2}, ..., z_{t-M} as measured RSSs at time t, $t-T$, $t-2T$, ..., $t-MT$, where M is the size of a time window. With an AR(1) model, the current value of RSS can be expressed as a linear aggregate of previous RSS values and an uncorrelated normal noise a_t with mean zero and variance σ_a^2. Let μ be the average RSS in a time window and $\tilde{z}_t = z_t - \mu$, then

$$\tilde{z}_t = \emptyset \tilde{z}_{t-1} + a_t. \tag{2}$$

Using Yule-Walker equations [14], the model parameter (ϕ) becomes an autocorrelation of $\tilde{z}_t$ at lag-1 (ρ_1) and the variance of a_t is given as

$$\sigma_a^2 = E[\tilde{z}_t^2](1 - \emptyset\rho_1) = r_0(1 - \emptyset^2) \tag{3}$$

From the time-series theory, the optimal k-step ahead predictor at time t in the sense of minimum mean square error is the conditional expectation $E[\tilde{z}_{t+k}|\tilde{z}_t, \tilde{z}_{t-1}, ...]$. In the case of AR(1) process, k-step ahead predicted RSS at time t ($\tilde{z}_{t+k}$) is given as

$$\hat{z}_{t+k} = \mu + \emptyset^2 \tilde{z}_t + e_k, \tag{4}$$

where e_k is the k-step ahead RSS prediction error. From Eq.(2), e_k follows a normal distribution with mean zero and variance

$$\sigma_{t+k}^2 = \sigma_a^2 \sum_{i=0}^{k-1} \emptyset^{2i}. \tag{5}$$

The predictability of $\hat{z}_{t+k}$ is defined as the minimum error (e_m) that satisfies given error tolerance probability, x (*i.e.*, $Pr(|e_k| < e_m) \geq x$). Given x, the $\hat{z}_{t+k}$ is said to be more predictable as e_m becomes smaller. If we denote the cumulative distribution function of the standard normal distribution by F(·), the e_m becomes

$$e_m \geq \sigma_{t+k} F^{-1}\left(\frac{1+x}{2}\right). \tag{6}$$

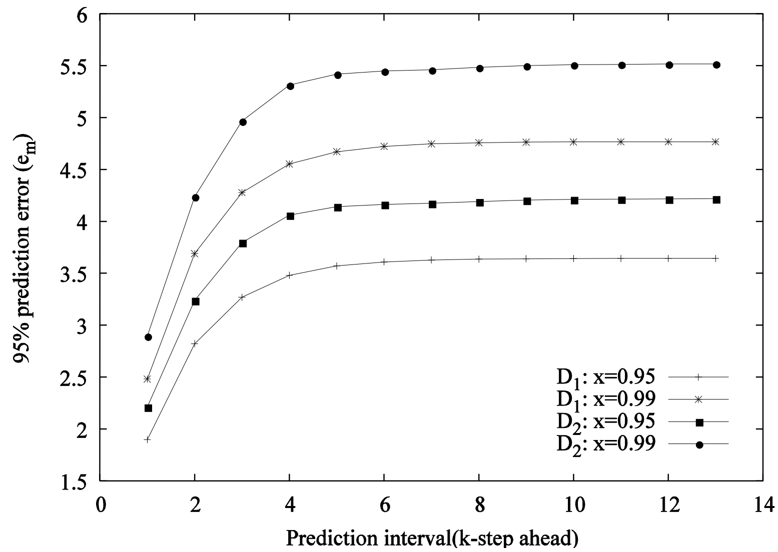

Figure 4. 95% of prediction error satisfying given error tolerance probability and prediction interval

Figure 4 shows 95% of e_m for $D_1$and D_2 that satisfies the given error tolerance probability (x) and prediction interval (k). 95% of 1-step ahead prediction error is less than 2.9dB even the error tolerance probability is 0.99. Considering that the measured RSS ranges from -120dB to -40dB, 2.9dB prediction error is small. For example, if a handoff process is executed when measured RSS is below -90dB, 2.9dB is only 3.2% of the threshold.

Given (e_m, x), the forecast error at time *t* should be bounded as

$$\Pr(|\hat{z}_{t+k} - z_{t+k}| > e_m) = \Pr\left(\left|\frac{\hat{z}_{t+k} - z_{t+k}}{\sigma_{t+k}}\right| > \frac{e_m}{\sigma_{t+k}}\right) \leq x. \quad (7)$$

Therefore, when (e_m, x) is given, the maximum predictability interval (k^*) is obtained by combining Eqs.(2), (3), and (5) into Eq. (7).

$$k^* = \left\lfloor 1 + \frac{1}{2}\log_{\emptyset}(1 - \frac{e_m^2(1 - \emptyset^2)}{\sigma_a^2(F^{-1}(1 - x/2)^2})) \right\rfloor, \quad (8)$$

where $\lfloor y \rfloor$ is the largest integer that is smaller than y. Because the absolute value of AR(1) model parameter (ϕ) should be less than 1 for the process to be stationary, we can always predict 1-step ahead of RSS if the following condition is satisfied.

$$\frac{\in^2 (1 - \emptyset^2)}{\sigma_a^2(F^{-1}(1 - x/2)^2} \leq 1. \quad (9)$$

3.2 Handover Trigger

L2 triggers may be initiated if $\hat{z}_{t+k}$ is smaller than the RSS threshold (T^*_{rss}). Here, T^*_{rss} is assumed to be determined by a given target handoff delay. If $\hat{z}_{t+k}$ is overestimated, however, L2 triggers may be initiated too late to meet the given target handoff delay. Therefore, the prediction error must be considered in handoff decision process to reduce the rate of late L2 triggers.

Adequate compensation of T^*_{rss} can be helpful to avoid the overestimation and the subsequent late L2 triggers. Because the prediction error follows normal distribution with mean zero and variance σ^2_{t+k}, the $(1-y)$100% prediction limit for the *k*-step ahead RSS is given by

$$\hat{z}_{t+k} - z_{y/2}\sigma_{t+k} \leq z_{t+k} \leq \hat{z}_{t+k} + z_{y/2}\sigma_{t+k}, \tag{10}$$

where $z_{y/2}$ is the *z*-value leaving the area of *y*/2 to the right in the probability density function (pdf) of the standard normal distribution. By Eq. (10), if T^*_{rss} is compensated for the $(1-y)$ 100% prediction error, the compensated RSS threshold (T^k_{rss}) is given by

$$T^k_{rss} = T^*_{rss} + z_{y/2}\sigma_{t+k} \tag{11}$$

By the compensation, a L2 trigger is initiated only if $\hat{z}_{t+k}$ is smaller than T^k_{rss}.

4. Performance Evaluation

We have conducted ns-2 simulations to investigate the performance of our handover triggering method. In our simulations, APs are deployed along a 100 by 100 rectangular grid, and each distance between APs is set to 34 meters in consideration of the radio propagation characteristics in the obstructed area (O). For 48 hours, a MN moves on the grid freely following the random waypoint model with the maximum speed of 10km/h [11]. The time window size (M) is set to 10. In order to show the robustness of the compensation, the same simulations are repeated 10 times with different mobility patterns and all the results from the 10 simulations are averaged.

Figure 5 shows the rate of late L2 triggers when the prediction limit ranges over 0 through 90%. Two different values of the measurement interval (T) are considered; 0.5sec and 1sec. For each value of T, the target handoff delay (t_h) is set to make the ratio between t_h and T be 1 or 2 so that the 1-step or 2-step ahead prediction is required. Without the compensation (i.e. when the prediction limit is 0), almost all the L2 triggers are initiated late. On the other hand, as the prediction limit increases, the rate of late L2 triggers drops rapidly. The rate is maintained below 4.8% for the prediction limit exceeding 80%, regardless of the values of t_h and T. Given the same prediction limit, the number of prediction step (*k*) has a major effect on the rate of late L2 triggers. For example, when t_h = 1 and the prediction limit is 60%, the rate of late L2 trigger is 57.73% in case of the 2-step prediction (T = 0.5) while 2.05% in case of the 1-step prediction (T = 1).

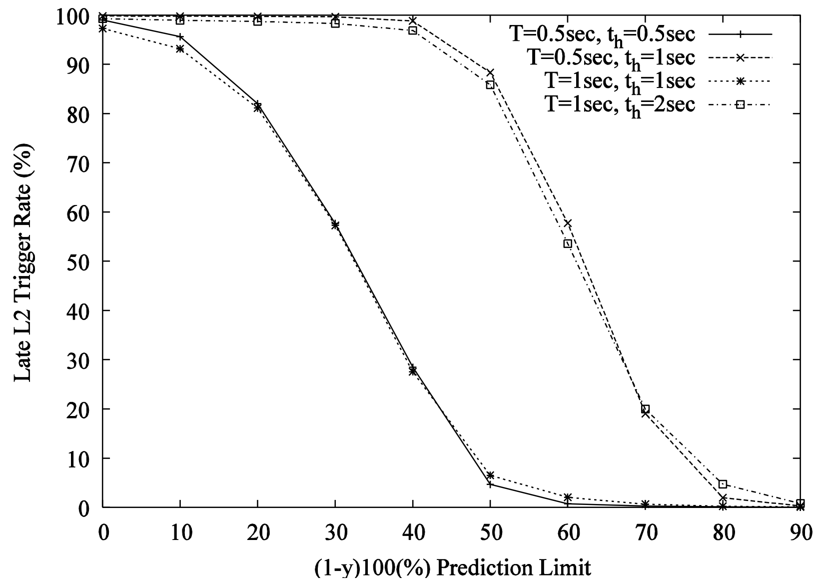

Figure 5. The rate of late L2 triggers for (1 − y)100% prediction limits

Figure 6 shows a pedestrian holding a mobile device is walking (from the center) toward the cell boundary. Our handoff triggering method initiates a L2 trigger when the pedestrian passes the point A if $\hat{z}_{t+k}$ at point A is smaller than T^k_{res}. The RSS value measured next may rather increase after the L2 trigger has been initiated. This premature L2 trigger is called 'false alarm'. Since the false alarm may not correspond to a handoff, it may harm the overall system performance due to the system resource waste, the additional processes, and *etc.* Therefore, another simulations have been conducted with the environments and parameters that are the same as for the rate of late L2 triggers, and the results are shown in Table 1.

As can be seen in Table 1, the overall false alarm rate is not so significant for all the values of the prediction limit, which can be explained as follows. For example, it is observed that 95% of the 1-step prediction error corresponds to 2dB increment in RSS values when the prediction limit is 80%. That is, assuming that $\hat{z}_{t+k}$ at point B is T^k_{res}, the RSS at point A is higher than at point B as much as 2dB. By the path loss model [13] for the obstructed area, 2dB difference in RSS corresponds to only 2 meters (*i.e.*, d = 2 in Figure 6). Note that it takes only 1.44sec for a pedestrian walking at the speed of 5km/h. During 1.44 seconds, it is not so likely for the pedestrian to change its direction.

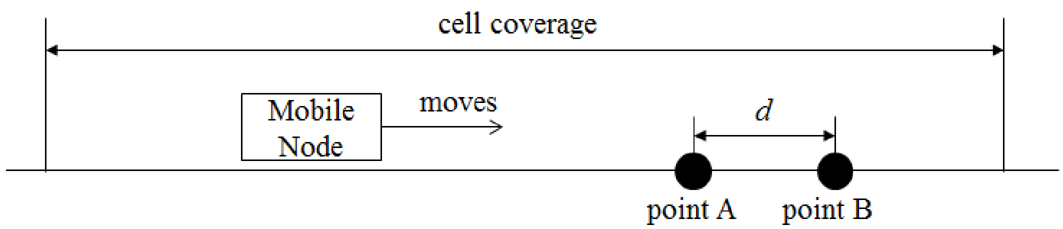

Figure 6. False alarm initiation

Table 1. False alarm rate (%) for the prediction limits

(1 − y)100(%)	50	60	70	80
T = 0.5sec, t_h = 0.5sec	0.293	0.751	1.293	1.935
T = 0.5sec, t_h = 1sec	0	0.009	0.1998	0.708
T = 1sec, t_h = 1sec	0.603	1.493	2.304	3.399
T = 1sec, t_h = 2sec	0	0.152	0.57	1.489

5. Conclusion

In this paper, through statistical investigation of measured RSS values, we verify that an adaptive AR(1) process can be used to model a set of consecutive RSS values. We also present analytically the predictability of measured RSS values that even though RSS values changes abruptly, the *k*-step ahead RSS value can be predicted with a given error tolerance level by applying the AR(1) model to the measured RSS values in a time window.

In our simulation studies, we show that even the 1-step ahead RSS prediction error is small, most of L2 triggers are initiated later than given target handoff delay if the error is not controlled. Thus, we also propose how the prediction error can be controlled to reduce late L2 trigger rate. We have shown that the rate of late L2 triggers can be significantly reduced by compensating the prediction error. Although the number of false alarms increases a little, we believe that the increase may be regarded as trivial considering the significant decrease in the late L2 triggers.

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