Wavelet Based Detection of Shadow Fading in Wireless Networks

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***Abstract*— In wireless communications, shadow fading can cause at least 6 dB power loss for 10% of the time [1]. Early detection of shadow fading plays an important part in facilitating the design of adaptive data transmission schemes. We propose an accurate, on-line detection mechanism to detect a receiver entering or leaving shadow regions using simply signal strength measurements. The method is based on wavelet decomposition of signal strength time series into independent fading components. Our measurements indicate that fast fading signals have a scale invariant nature. This scale invariance of fading signals is destroyed when shadow fading, which is log-normal distributed and is independent of fast fading components, is added to the signal. An online detection mechanism is then proposed which exploits this phenomenon. Real measurements of signal strength traces are used to validate the detection mechanism.**

I. INTRODUCTION

Knowledge of rapidly time variant fading channel conditions not only helps wireless propagation modeling in simulations but also enables adaptive data transmission in wireless systems. Multipath fading (also called small scale fading) causes changes in the received signal strength within the order of one wavelength. Shadow (medium-scale) fading is influenced by the spatial movements in the order of tens of wavelengths and creates random variations in the average power of the received signal. Path loss (large-scale fading) is caused by spatial movements in the order of hundreds of wavelengths making the average power level vary in power-law fashion with path length. [3]. The above three fading components are mutually independent of each other.

In general, the received signal strength in wireless networks is not an ergodic process not only because the channel is susceptible to noise and interference, but also because of unpredictable user movement. The location, size and material of encountered surrounding obstacles which cause fading are generally unknown. In this paper, we present a method to quickly detect signal magnitude changes caused while a mobile node is walking in or out of shadowing, using received signal strength as input to our detection mechanism. The work is motivated by the fact that shadowing causes degradation of received power magnitude and adds more variations to the channel quality. An early detection of shadowing helps the design of protocols for adaptive data transmission.

Our shadowing detection method is based on examining for scale-invariance in the received signal strength time series using wavelet transform analysis. By analyzing wavelet coefficients at different scales extracted from our experimental data trace, we first show that multipath fading signals have properties of scale-invariance. The scale-invariance property of signal strength trace is destroyed to some extent when shadow fading occurs which adds log-normal distributed variations and leads to abrupt changes in the trace. We then detect the instances of a receiver entering or leaving shadowing regions by detecting the absence or presence of scale-invariance in the signal strength trace. By measuring the deviation from linearity when the wavelet coefficients are considered as a function of the scale in log-log domain, shadow fading is detected and alarms are generated.

The rest of the paper is organized as follows: Section II presents the related work. Section III presents the experimental setup. Section IV describes the proposed methodology for shadowing detection. Section V validates the method on real signal strength measurements in several scenarios with shadowing obstacles. Finally, Section VI presents the concluding remarks.

II. RELATED WORK

The impact of shadowing in wireless systems has been widely studied in recent years. In [1] the impact of body shadowing on a proposed OFDM system for an indoor wireless LAN is studied. It's pointed out that for indoor applications, the shadowing caused by persons walking across the LOS can severely degrade the link performance. The importance of shadow fading in handover decision making in cellular networks is shown in [3]. The variation of signal fading caused by shadowing has been experimentally found to lie between 4-12dB. In [5] the performance of CSMA/CD protocols is studied under the impact of multipath and shadow fading. A better understanding of fading channels helps the design of MAC protocols. Also, the fact that shadow fading causes degradation of the wireless channel quality motivates our work to develop an efficient on-line shadowing detection mechanism.

Among various wireless channel estimation techniques, wavelet decomposition is an elegant tool for fading signal estimation and prediction. In [6] the authors construct a spectrum decomposition based on Slepian semi-wavelet that can be used to recover and predict the fading envelop of the channel transfer function in mobile radio networks. The authors of [7] develop a one-dimensional wavelet network (WN) for comb-type pilot arrangement channel estimation.

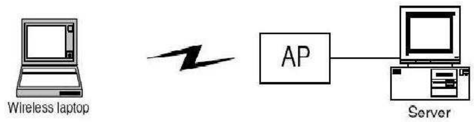


Fig. 1. Experiment setup

The authors demonstrate that their wavelet based channel estimation methods exhibit an improved performance compared to the conventional linear channel estimation methods and are robust to fast fading channels.

In [8] scale-invariance and Long Range Dependence (LRD) phenomenon in telecommunications traffic is explored. A LRD test tool is provided by Patrice Abry and his colleagues, which may be used to visualize the scaling behavior of data using a logscale diagram [**?**]. In our work, we show that the fast fading signal in wireless networks also exhibit scale-invariance property for a number of scales that can be utilized to detect shadow fading.

III. Signal Strength Measurement Methodology

In this section we outline the methodology applied to obtain the traces of the signal strength for the purposes of the detection algorithm developed in this paper. The measurements were conducted in the building of Johnsson Engineering Center of RPI which primarily consists of rooms for faculty and space for laboratories. In the floors of this building where the measurements were conducted, metallic doors, metallic filing cabinet and concrete walls were the primary sources of shadowing. Multiple traces for the signal strength were collected as the user walked around and passed the several shadowing obstacles. The points when shadowing regions are encountered were recorded in order to validate our detection mechanism.

Figure 1 shows the basic setup used for the measurements. Signal strength measurements were done using a LINKSYS Wireless-G Broadband Router as the access point (AP) and IBM T42 laptop, running Linux Feroda core 5, with built in PH12127-E IBM 802.11a/b/g Wireless LAN Mini PCI adapter as receiver. The signal strength measurements were directly provided from the card by the `madwifi`-0.9.2 driver used for the card. The driver uses RSSI as the basic measure for signal strength which is converted to dBm. The driver assumes a constant noise level of -96dBm since this is the thermal noise for 20MHz OFDM signals, plus an additional 5dBm noise from the amplifiers. The SNR levels are then obtained by SNR(dBm)=Signal(dBm)-Noise(dBm). The actual signal strength measurements were conducted while the laptop received packets from the AP. The packets were from an UDP video data stream transmitted at a data rate of 54Mbps in 802.11g wireless network. We collected signal strength measurement every 0.01 seconds.

IV. Methodology

A. Overview

The goal of our shadowing detection methodology is to isolate shadow fading from a fading signal trace and detect its occurrence. We use wavelet decomposition to analyze multipath fading and shadow fading separately at their proper scales. We explore the scale-invariance nature of multipath fading and show that such a property is absent for shadow fading. A shadowing detection mechanism is then developed by detecting the absence or presence of scale-invariance property in the signal strength trace.

B. Propagation Model

For the purposes of this paper we use the following commonly used statistical model from [2]. The ratio of the received and transmitted powers, P_r and P_u respectively, in dBm is given by

$$\frac{P_r}{P_u}(\mathrm{dBm}) = 10\log_{10} K - 10\gamma\log_{10}\frac{d}{d_0} + \varphi_{\mathrm{dBm}} + \phi_{\mathrm{dBm}} \quad (1)$$

where $10\gamma\log_{10}\frac{d}{d_0}$ models the path loss fading as a linear function of distance d between the transmitter and receiver, with d_0 being the reference distance. Also, γ is the path loss exponent and K is a unitless constant which depends on the antenna characteristics. The attenuation from shadowing, φ_{dBm}, is normally distributed with zero mean and variance σ_φ^2. Finally, ϕ_{dBm} represents the variation caused by multipath fading following a Raleigh distribution. A segment of multipath fading signal trace can be assumed to be quasi stationary.

C. Wavelet Decomposition

In our work we use wavelet transform to decompose a fading signal trace into its three independent components: multipath fading, shadow fading and path loss fading. Wavelet transform provides the time-frequency representation of the signal at different scales. A signal can be presented by its approximation at any scale (octave) J where $1 \le J \le J_{MAX}$ ($J_{MAX} = \log_2(n)$ is determined by the length, n, of the time series), plus all the details at lower scales $j, 1 \le j \le J$. The wavelet decomposition formula is given by

$$\begin{aligned} x &= \mathrm{approx}_J + \sum_{j=1}^{J} \mathrm{details}_j \\ &= \sum_k a_x(J,k)\phi_{J,k} + \sum_{j=1}^{J}\sum_k d_x(j,k)\varphi_{j,k} \end{aligned} \quad (2)$$

where $a_x(j,k)$ and $d_x(j,k)$ are the wavelet transform approximation and detail coefficients respectively, at scale j and time k. $\phi_{J,k}$ is the wavelet function transformed from the mother wavelet function ϕ and $\varphi_{j,k}$ is the scale function. As an example, Figure 2 shows that our experimental fading signal strength trace x may be decomposed into an approximation at octave $J = 5$ ($a5$) plus all the details at octave $j = 1, \cdots, 5$ ($d1, \cdots, d5$). For our experimental data, there are 3000 samples in the trace, which covers about 100 meters walking distance, so our sampling rate is 0.033m/sample. At 2.437GHz frequency (channel 6 in IEEE 802.11g), the radio wavelength is 0.1231m. At octave 5, the signal trace is presented by only 75 samples (1.33m/sample), which means that the time resolution of the signal approximation at octave

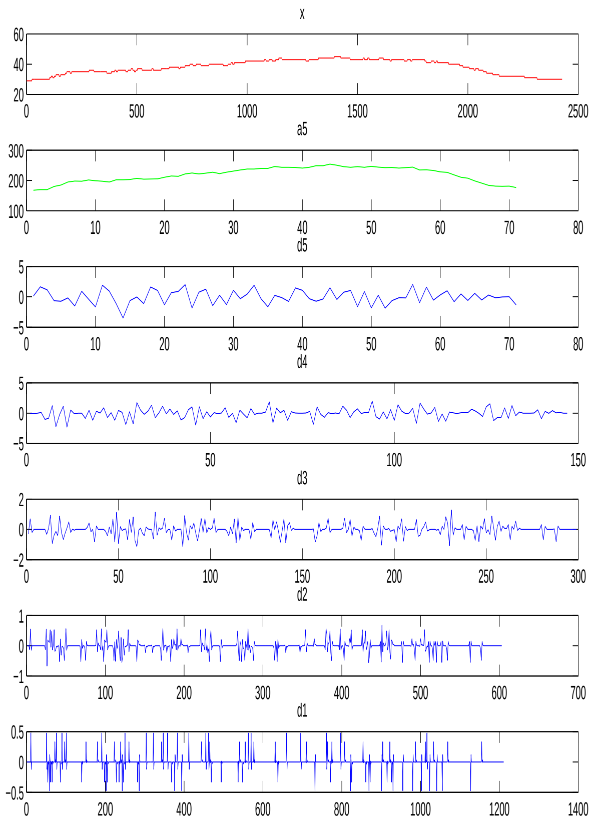


Fig. 2. Wavelet decomposition at level 5: x=a5+d4+d4+d3+d2+d1

5 is about ten times the wavelength, which corresponds to the shadow fading scale. For octaves 1-3, the time resolution of the signal is of the order of a wavelength, and therefore corresponds to multipath fading. Octave 4 corresponds to the transition region between medium and small scales. Large scales are octaves larger than 6 which correspond to path loss fading and is not the focus of this work.

D. Scale-Invariance Property of Signal Strength Under Fast Fading

The property of scale invariance is defined as when there is no controlling characteristic scale or equivalently when all scales have equal importance. Wavelet decomposition is a useful tool for analysis, estimation and detection of scale-invariant processes. Fundamentally this is due to the "non-trivial fact that wavelet family itself possesses a scale invariant feature a property not shared by other analysis methods" [9]. We analyze the scale invariant nature of our experimental fading signal strength trace using wavelet transform. To calculate the energy at different scales for the signal strength trace, a sliding window is defined and moves along the data trace. For each data segment x within the sliding window, n_j wavelet coefficients $d(j,k), k = 1, \cdots, n_j$ are obtained for each octave j. For each j, $d(j,\cdot)$ is a stationary, short range dependent

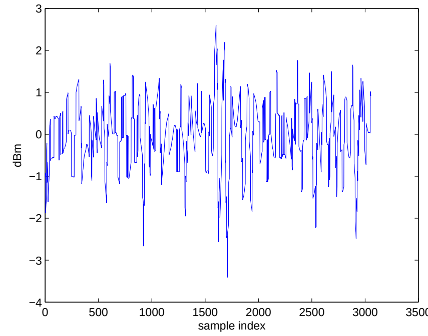


Fig. 3. Fading signal strength

process with zero mean. Let μ_j be the time average of the wavelet coefficients $d(j,\cdot)^2$ for x at octave j given by

$$\mu_j = \frac{1}{n_j} \sum_{k=1}^{n_j} |d_x(j,k)|^2 \tag{3}$$

The random variable μ_j is a non-parametric unbiased estimator of the variance of the process $d(j,\cdot)$ and is a near optimal way of presenting second order behavior of x at octave j. μ_j thus presents the energy of x at scale j. The μ_j at each scale is weakly dependent on other scales. As the sliding window moves, a trace of μ_j is obtained for each octave j. Figure 3 shows one of our measured fast fading signal strength traces x extracted from the signal strength measurement after removing the average. Figure 4 shows the traces of μ_j extracted for this trace at each octave j ($j = 1, \cdots, 6$) as the sliding window moves. The similar patterns at different scales in Figure 4 illustrate the presence of scale-invariance property for the fading signal trace. On the other hand, a normally distributed process doesn't have the scale-invariance property. Figure 5 shows the trace of μ_j at different scales for an independent Gaussian process, where the scale-invariant property is absent.

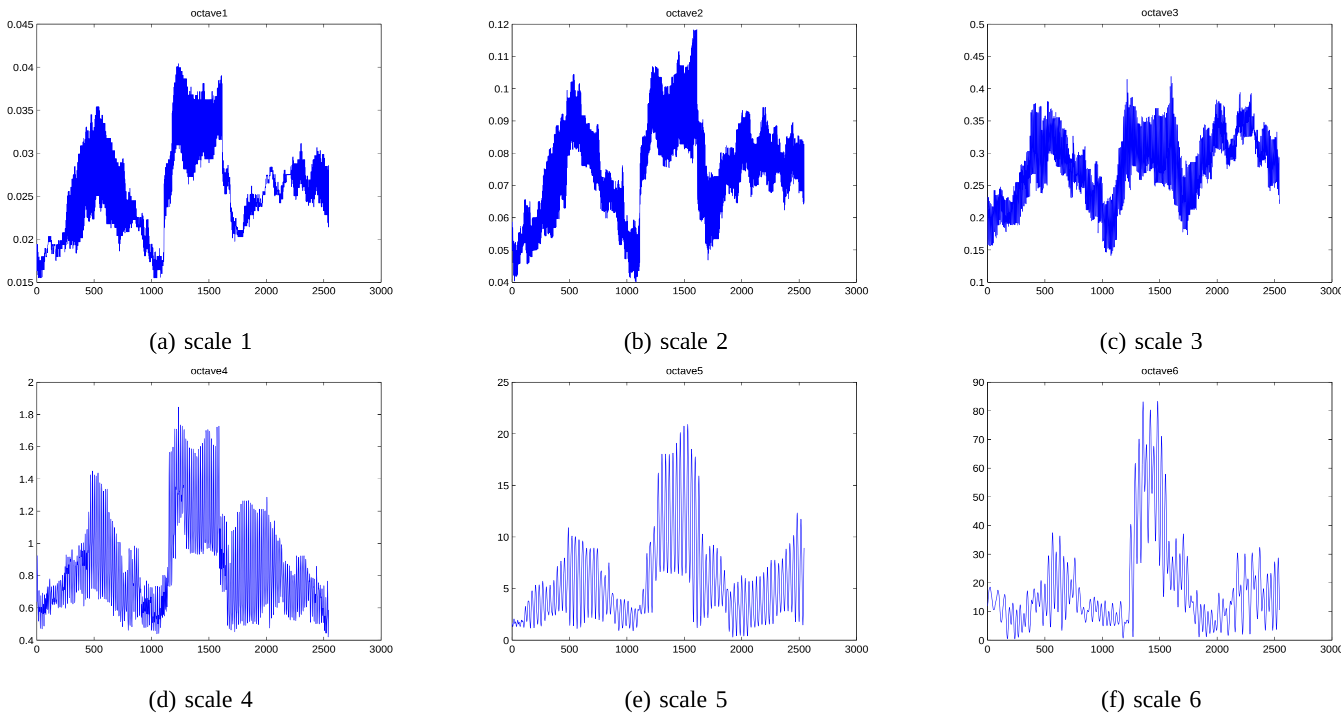
E. Shadowing Detection Algorithm

In this section, we develop an algorithm to detect the instances when a receiver enters or leaves shadowing regions by detecting the absence or presence of scale-invariance in the signal strength trace. This is based on the fact that multipath fading signal has scale-invariance property, which is destroyed when log-normal distributed shadow fading is encountered, which adds more variations and leads to abrupt changes in the signal strength trace.

The underling principle of our scale-invariance test tool is given by

$$y_j = \log_2(E(d_x(j,.))^2) = j\alpha + \log_2(C) \tag{4}$$

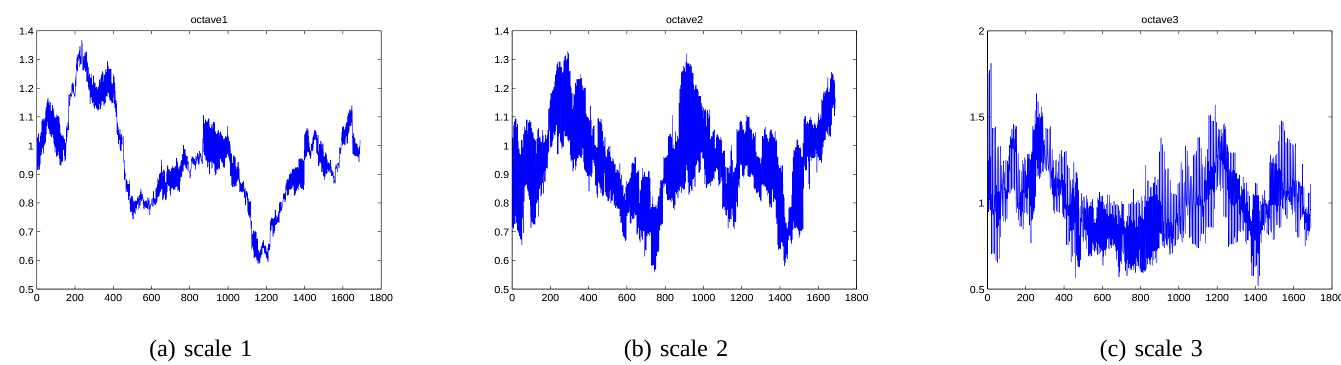
where $y_j = E(d_x(j,.))^2 = \mu_j$ is generated by the wavelet coefficients and is given by Equation (3) and α and C are constants. Equation (4) shows that for scale-invariant processes, μ_j is a statistical linear function with j. This suggests a linear regression approach for detection of scale-invariance properties by measuring the linearity of function y_j in log-log domain. To show further evidence of the scale invariance,



(a) scale 1 (b) scale 2 (c) scale 3

(d) scale 4 (e) scale 5 (f) scale 6

Fig. 4. Scale-invariance property hold for a wide range of scales for fast fading signal



(a) scale 1 (b) scale 2 (c) scale 3

Fig. 5. Scale-invariance property is absent for Gaussian processes

in Figure 6 we plot y_j against j along with the confidence intervals for y_j in a logscale diagram for a measured multipath fading trace without shadowing. Scaling behavior is detected through the existence of an alignment region, where for a range of scales $j_{min} \leq j \leq j_{max}$ the confidence interval of y_j falls on the linear regression line. The plot of y_j in Figure 6 fits well with its linear regression line and indicates presence of scale-invariant property of our multipath fading trace. The corresponding logscale diagram for a trace containing shadow fading is shown in Figure 7. The figure shows the deviation of the log-log plot from its linear regression line for octave 4 and 5. The angle θ (shown in Figure 7) can be used as a measure of the non-linearity of function y_j.

In our detection mechanism, a sliding window with size 2^8 is defined and moves along the data trace. For each segment x within the sliding window, linearity of y_j as a function of octaves j in log-log domain is measured through calculating

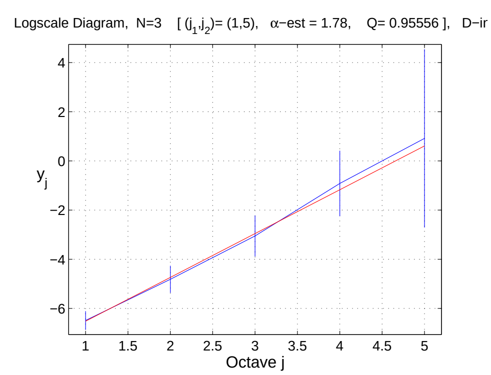


Fig. 6. Linear log-log plot without shadowing

the angle θ by

$$\theta = |\pi + \arctan(y_J - y_{J-1}) - \arctan(y_{J+1} - y_J)| \qquad (5)$$

where J=4 is used in our algorithm since octaves of $J > 4$ correspond to shadow fading. When the value of θ exceeds

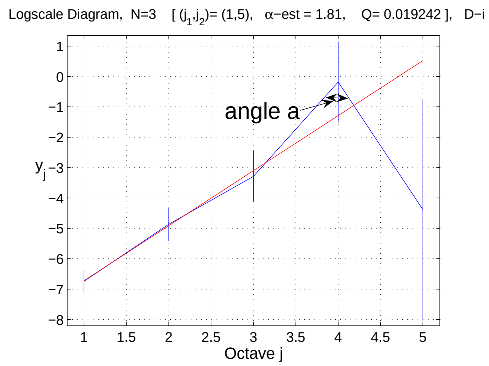


Fig. 7. Non-linear log-log plot when shadowing occurs

an empirical threshold θ_{MAX}, change in the scale-invariance property is detected which indicates the occurrence of shadow fading and alarms are generated. Our detection algorithm is given in algorithm 1.

Algorithm 1 Shadowing Detection Process

x: `signal strength trace`;
$x(i)$: `ith sample in signal strength trace`;
y: `data segment`;
$w = 2^8$: `sliding window size`;
t: `linearity measurement result`;
T: `linearity measurement threshold`;
DATA TRAINING
use training signal trace set to obtain empirical threshold parameter T;
DATA TESTING
$k = 1$: `initially start index is set to 1`;
$y = x(1 : w-1)$: `obtain initiate data segment`;
repeat
  get new measurement data $x(k + w - 1)$;
  $y = x(k : k + w - 1)$;
  obtain log-log plot L for y;
  calculate linearity measurement t on L.
  if $t > T$ **then**
    report $x(k + w - 1)$ as detection of shadowing;
  end if
until monitoring process terminated

V. Experimental Results

To validate our shadowing detection mechanism, we consider different types of shadowing objects in three scenarios. In scenario one shown in Figure 8 scenario (a), an AP was placed behind a metallic cabinet in an office. A human user with a laptop or the receiver walked in the aisle toward the AP, passed the metallic cabinet, then walked further away from the AP. Our detection result is shown in Figure 8 result (a), where '*' marks indicate the instances when alarms are generated. The shadowing area is labeled in the figure. As can be seen, alarms are generated when a user is entering as well as leaving the shadowing region.

In scenario two shown in Figure 8 scenario (b), the AP was placed in a lab with a metallic door closed. The user walked on the hallway outside the lab, passed the metallic door which acted as the first shadowing object, then continued to walk and passed another half of a parallel metallic door in the hallway, which acted as the second shadowing object. Our detection result is shown in Figure 8 result (b) with the shadowing areas labeled. We note that our detection mechanism is able to detect both the shadowing objects.

In scenario three shown in Figure 8 scenario (c), the AP was placed in an office. The receiver walked on an aisle in front of the office with a concrete wall in between the receiver and AP. A metallic door was passed in the beginning of trail. Our detection result in Figure 8 result (c) shows that the proposed mechanism is able to detect the instance when the user enters and leaves the shadowing region caused by the metallic door. Our mechanism is also able to detect the instant when the user moves out of the shadowing caused by the concrete walls. A few false alarms are generated at the end of the trace, which is due to the finite length of time series data in wavelet analysis. If the user moves continuously, such false alarms will not be generated.

VI. Conclusions

This paper proposes an accurate, on-line mechanism for detecting shadow fading in wireless networks. The detection method is based on wavelet decomposition of fading signal time series. We show that fast fading signals are scale invariant, a property which is absent in signals with log-normal distributed shadow fading. We detect instances where the receiver enters or leaves shadowing regions by detecting the absence or presence of scale-invariance in the signal strength trace.

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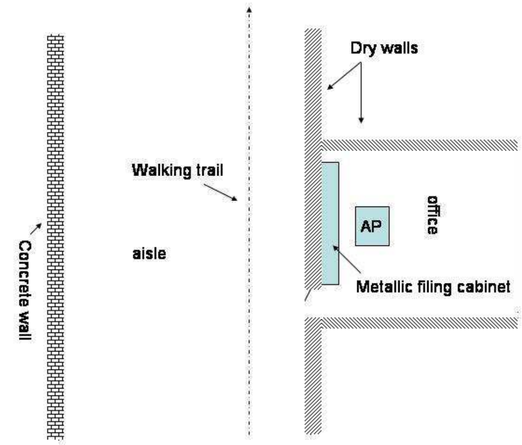
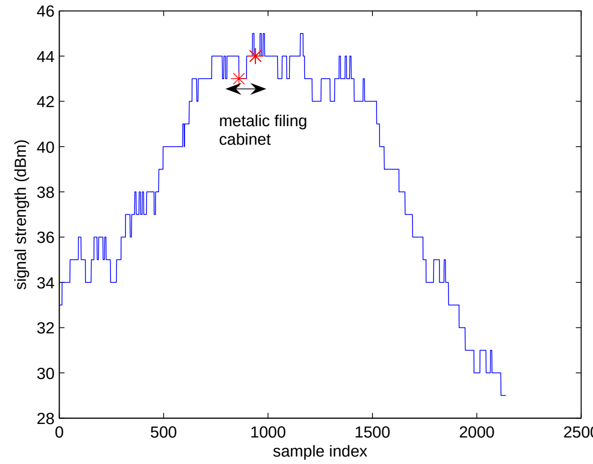
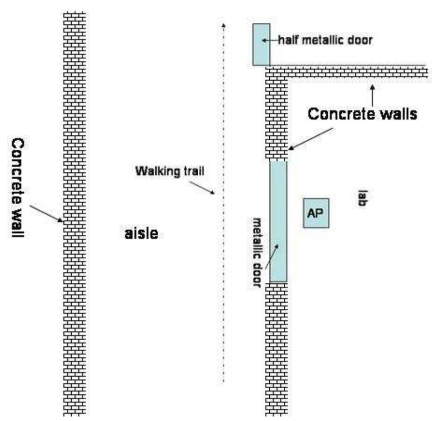


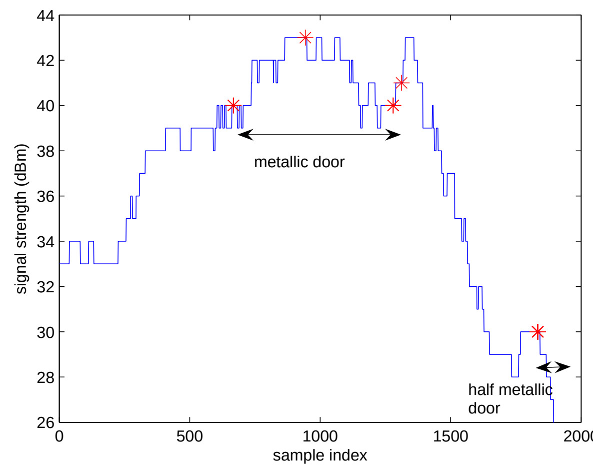
scenario (a)



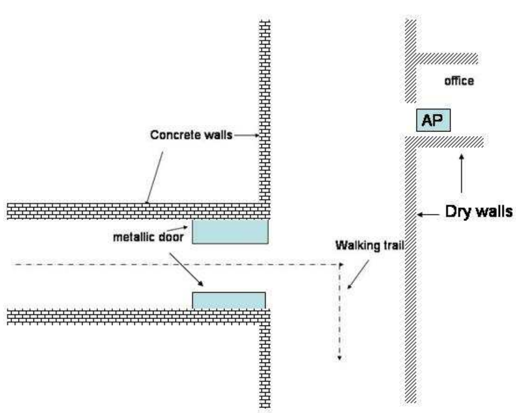
result (a)



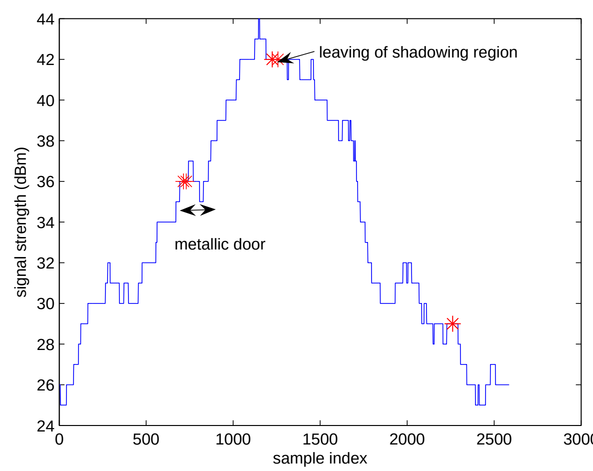
scenario (b)



result (b)



scenario (c)



result (c)

Fig. 8. Experimental scenarios and shadowing detection results