Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering (ICCSEE 2013)

MIMO-OFDM NLOS Identification Algorithm Based on Hypothesis Test

Weibo Zhao, You Zhou, Hanying Hu
Institute of Information Technology,
Zhengzhou, China,
zhaoweibo_1@hotmail.com

***Abstract*—A NLOS identification algorithm based on rician K-factor hypothesis test was proposed to mitigate position location bias caused by NLOS propagation in MIMO-OFDM system. A multi-antenna rician K-factor estimation method was derived from the correlation difference of deterministic and diffuse component between antennas. A rician K-factor decision model was established according to signal propagation environment. The identification result was derived from the decision model with the estimated K-factor. Simulation results showed that the proposed algorithm could achieve good identification performance even when K was small and had a good robustness to antenna configuration and scattering distribution.**

Keywords-Position Location; MIMO-OFDM; NLOS Identification; Hypothesis Test; Rician K-factor

I. INTRODUCTION

Wireless localization has a wide range of civilian and military applications including battle filed command and control, fire fighter tracking, emergency positioning, road traffic alert and ad-hoc network resource arrangement [1]. Existing location technologies are mainly based on time of arrival (TOA), degree of arrival (DOA) and received signal strength indication (RSSI) [2], which are very sensitive to the availability of line-of-sight signal. When LOS is not available, NLOS signal travels longer distances compared with the LOS path, target position will result in big bias due to a larger TOA and a wrong DOA estimation. An available solution on NLOS mitigation is to identify signal LOS status before localization computation.

NLOS identification can be multi-station cooperative [3] or single-station non-cooperative [4] solutions. Multi-station identification could achieve good performance only when there are adequate LOS stations. Cooperative method also has a high computational complexity compared to non-cooperative method. Single station identification can works in the absence of LOS measurements and precise location of other stations. Single station identification method including TOA statistical based, channel characteristics based and hybrid measurements based approaches. TOA statistical approach [5] requires high SNR and long process time to identify signal LOS status. Hybrid approach [6] requires joint measurement including TOA, DOA and RSSI, it could achieve high performance while it requires high hardware complexity. Taking advantage of channel characteristics like signal strength, power delay distribution and rician K factor, channel characteristics based approach [7] [8]could maintain a good trade-off between requirements and performance.

This paper proposed a multi-antenna NLOS identification algorithm. Taking rician K factor as target characteristics, this paper combined signal propagation model and channel characteristics based identification method in order to identify signal status in multi-antenna systems. Firstly, a rician K factor estimation approach aimed at multi-antenna system was proposed. Secondly, NLOS identification based on hypothesis test was established according to different distribution of rician K factor in LOS and NLOS scenarios. Finally, the NLOS identification result could be achieved through comparing the estimated K factor and hypothesis test decision threshold. Compared with conventional identification method, this algorithm can achieve good efficiency taking advantages of multi-antenna received data.

II. SYSTEM MODEL

Rician channel impulse response can be defined by:

$$h_i(t) = \left(a_i^s + a_i^d\right)\delta\left(t-\tau\right) \qquad (1)$$

where $h_i(t)$ is the channel impulse response of antenna i, a_i^s is the specular component and a_i^d is the diffusive component, which is a random Gaussian complex variable [9]. Assuming the observed rician K factor in different antennas $\Omega_i = \left|a_i^s\right|^2 + E\left[\left|a_i^d\right|^2\right]$, $K = \left|a_i^s\right|^2 / E\left[\left|a_i^d\right|^2\right]$, so $h_i(t)$ could be express as follows:

$$h_i(t) = \sqrt{\frac{\Omega_i K}{K+1}}\exp\left\{-j2\pi f_D \sin\left(\theta_0-\theta_\alpha\right)t+\phi_0\right\} + \sqrt{\frac{\Omega_i}{K+1}}\tilde{a}_i \qquad (2)$$

where f_D is maximum Doppler spread, θ_0 and θ_α are respectively the angle of arrival and the phase of the LOS component. $\tilde{a}_i(t)$ is normal diffusive component, i.e. $E\left[\left|\tilde{a}_i(t)\right|^2\right]=1$, $h_i(t)$ will turn into Rayleigh channel when rician K factor is zero.

For MIMO-OFDM system, we could get channel impulse response for each subcarrier and the frequency impulse response could be express as follows considering noise effect

$$\hat{H}_i(t) = \left(a_i^s + a_i^d\right)\exp\left(-j2\pi n\Delta f\tau\right) + W_i \qquad (3)$$

where n and Δf are subcarrier number and frequency interval, W_i is the noise component.

III. MULTI-ANTENNA RICIAN K FACTOR ESTIMATION ALGORITHM

Conventional rician K factor estimation was based on single antenna and suffers from envelope estimation bias when K increases. For multi-antenna system, received data from different antennas is not independent any more, which provides an opportunity to divide specular and diffusive components.

Assuming that noise components are independent among different antennas and the coherence of diffusive components among antennas is dependent on antenna array type, antenna spacing, signal arrival direction, arrival degree power distribution and angle spread (AS) [10]. We can assume that diffusive components are independent when antenna spacing is large than half wavelength. Defining $M_l(i,j)$ is the $l-th$ order channel impulse response cross-moment matrix of antenna i and j, we can derive the fourth-order channel response matrix on the same antenna

$$\begin{aligned} M_4(i,i) &= E\left[\left|\hat{H}_i(t)\right|^4\right] \\ &= E\left[\left|H_i(t)\right|^4\right] + 4E\left[\left|H_i(t)\right|^2\right]E\left(\left|W_i\right|^2\right) + E\left(\left|W_i\right|^4\right) \\ &= K_R\Omega_i^2 + 4\Omega_i N_0 + K_W N_0^2 \end{aligned} \quad (4)$$

where $K_R = E\left[\left|H_i(t)\right|^4\right] / E\left[\left|H_i(t)\right|^2\right]^2$ and $K_W = E\left[\left|W_i\right|^4\right] / E\left[\left|W_i\right|^2\right]^2$ are respectively the rician channel and the noise kurtosises. The kurtosises of complex AWGN and rician channel are $K_\omega = 2$ and $K_R = 2 - \left(\frac{K}{K+1}\right)^2$ [11], and N_0 is equal to $E\left[\left|W_i\right|^2\right]$.

Similarly, we could derive the second-order moment on same and different antennas

$$M_2(i,i) = E\left[\left|H_i(t)\right|^2\right] = \Omega_i + N_0 \quad (5)$$

$$M_2(i,j) = \frac{K}{K+1}\sqrt{\Omega_i\Omega_j} \quad (6)$$

Using (4) and (5), we can obtain:

$$2M_2^2(j,j) - M_4(j,j) = \left(\frac{K}{K+1}\right)^2 \Omega_j^2 \quad (7)$$

$$\Omega_i / \Omega_j = M_2^2(i,j) / \left[2M_2^2(j) - M_4(j,j)\right] \quad (8)$$

and from (6) we can get:

$$\Omega_i - \Omega_j = M_2(i,i) - M_2(j,j) \quad (9)$$

Resolving the value of Ω of each antenna from (8) and (9):

$$\begin{aligned} \hat{\Omega}_j &= \left(\Omega_i - \Omega_j\right) / \left(1 - \frac{\Omega_i}{\Omega_j}\right) \\ &= \left(M_2(i) - M_2(j)\right) / \left(1 - \frac{M_2^2(i,j)}{2M_2^2(j) - M_4(j,j)}\right) \end{aligned} \quad (10)$$

The rician K factor is then deduced from (7) and (10):

$$\hat{K} = \frac{\sqrt{2M_2^2(j) - M_4(j,j)}}{\hat{\Omega}_j - \sqrt{2M_2^2(j) - M_4(j,j)}} \quad (11)$$

From (11) we can find that rician K factor is derived from multi-antenna data and we can get the mean K value when there are more than two antennas.

This section established a multi-antenna rician K factor estimation model, which took advantages of received data from multi-antenna and took the power difference of antennas and noise effect into consideration.

IV. RICIAN K FACTOR HYPOTHESIS TEST BASED LOS/NLOS DECISION ALGORITHM

A. Hypothesis test based decision algorithm

Rician K factor is defined as the power ratio of specular and diffusive components in received data. The K factor is a random variable in mobile communication varying from space channel parameters, which can be modeled as a stochastic variable with different distribution in LOS and NLOS environment. Then a NLOS decision model is proposed as follows

H_0： NLOS，distribution of K factor is $f(K_{NLOS})$

H_1： LOS，distribution of K factor is $f(K_{LOS})$

When MS is in LOS and NLOS status, the specular component power in dB is

$$\begin{aligned} P_r^{LOS} &= P_t - L^{LOS} \\ P_r^{LOS,pe} &= P_t - L^{LOS} - L_{pe} \end{aligned} \quad (12)$$

where P_r^{LOS}, P_t, L^{LOS} and L_{pe} are respectively the specular power, transport power, path loss in LOS and penetration loss, which are expressed in dB.

Similarly, the MS received power of diffusive component is

$$P_r^{NLOS} = P_t - L^{NLOS} - L_{sh} \quad (13)$$

where L_{sh} is the shadow fading loss of diffusive component.

Then the rician K factor expression could be derived according to its definition

LOS : $K_{dB}^{LOS} = P_r^{LOS} - P_r^{NLOS} = L_{sh} + L^{NLOS} - L^{LOS}$

NLOS : $K_{dB}^{NLOS} = L_{sh} - L_{pe} + L^{NLOS} - L^{LOS}$

Applying COST231 Walfisch-Ikegami [12] path loss to the signal power computation, we can describe the LOS path loss as follows

$$L^{LOS} = 42.6 + 26\log d + 20\log f_c \quad (14)$$

where d is the distance between base station and mobile station, and f_c is carrier frequency in MHz, while the NLOS path loss includes free space loss, street diffraction and shielding loss.

$$L^{NLOS} = L_d^{NLOS} + 38\log d \tag{15}$$

where L_d^{NLOS} is the sum loss besides free space path, which is affected by carrier frequency, antenna height and street width.

The authors in [13] modeled shadowing and penetration loss as lognormal stochastic variables, i.e. $L_{sh} \sim N\left(0,\sigma_{sh}^2\right)$, $L_{pe} \sim N\left(\mu_{pe},\sigma_{pe}^2\right)$, while $L^{NLOS} - L^{LOS}$ is decided only by channel parameters K_{dB}^{LOS} and K_{dB}^{NLOS} are both Gaussian distributed.

$$K_{dB}^{LOS} \sim N\left(L^{NLOS} - L^{LOS},\sigma_{sh}^2\right)$$
$$K_{dB}^{NLOS} \sim N\left(L^{NLOS} - L^{LOS} - \mu_{pe},\sigma_{sh}^2 + \sigma_{pe}^2\right) \tag{16}$$

Here, we develop a rician K factor distribution difference between LOS and NLOS scenarios and convert NLOS identification into a hypothesis test problem.

B. MS LOS/NLOS status identification with K factor

1) Known Prior Probability

The LOS and NLOS prior probability can be achieved from previous identification or environmental based empirical value. The decision rule can be expressed as follows

NLOS: when $f\left(K_{dB}^{NLOS}\right)P\left(H_0\right) > f\left(K_{dB}^{LOS}\right)P\left(H_1\right)$;

LOS: when $f\left(K_{dB}^{NLOS}\right)P\left(H_0\right) < f\left(K_{dB}^{LOS}\right)P\left(H_1\right)$;

2) Unknown Prior Probability

When the prior probability is not available, we can use the Neyman-Person test for hypothesis test decision. Setting the false alarm probability at $P_F = \alpha$, the decision threshold can be computed with NP test through the following formula

$$\alpha = \int_{-\infty}^{K_{th}} f\left(K_{dB}^{NLOS} = k\right)dk \tag{17}$$

V. SIMULATION RESULTS AND PERFORMANCE ANALYSIS

Simulations are conducted to investigate the performance of multi-antenna NLOS identification based on rician K factor. Simulations are based on multi-antenna OFDM systems, simulation parameters are set as follows: FFT number is 64, subcarrier bandwidth is 78.125KHz, the maximum time delay is 1000ns, SNR is 5dB, and the angle spread is assumed to be uniform distributed. The building height, BS and MS antenna height are 12m, 12.5m and 1.5m.

Fig. 1 shows the proposed multi-antenna rician K factor estimator performance compared to conventional single-antenna algorithm under different antenna configurations and scattering distributions. It is seen that our algorithm has a smaller RMSE though the RMSE increases slightly when K factor increase, while conventional K estimator RMSE increases greatly due to its algorithm sensitivity to envelop change. From the results under different simulation conditions we can find that the proposed algorithm also has a good robustness to antenna spacing and scattering distribution.

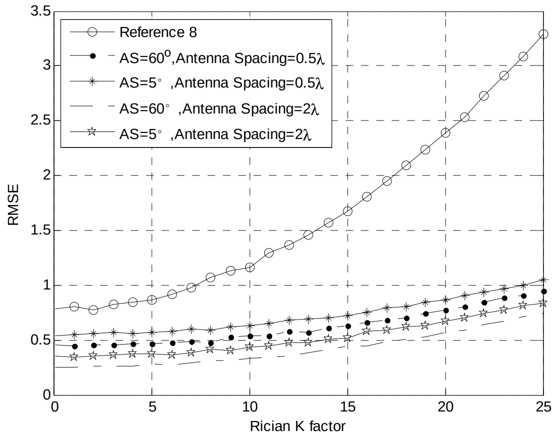

Figure 1. Rician K factor estimation RMSE of multi-antenna algorithm and conventional single-antenna metric

Next, the hypothesis test based NLOS decision algorithm performance is investigated. Fig. 2 and Tab. 1 show how the decision threshold changes along with different shadow fading when the prior probability is available. Fig. 3 shows the detection probability varies with false alarm probability under different shadow fading. The shadow fading is set at 4dB and 8dB respectively. Simulation results show when the shadowing standard deviation increase, the probability-of-error increase. While in the NP test, the curve of detection and false alarm probability moves to the upper left region when shadowing decreases, which means a better identification performance could be attained.

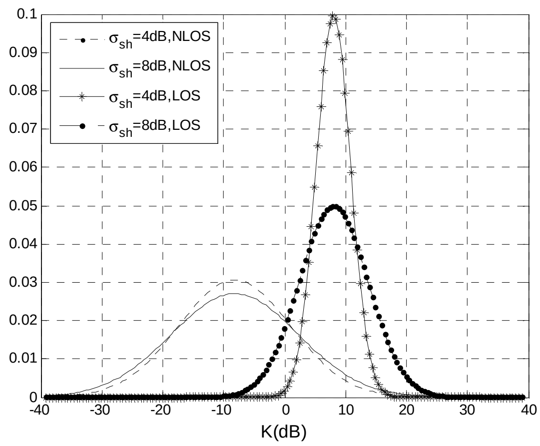

Figure 2. Decision threshold change of hypothesis test with different shadowing effects

Table 1. Decision threshold, false alarm and detection probability under different shadowing effects

	K_{th}	P_F	P_D
σ_{sh} =4dB	0.24dB	0.086	0.795
σ_{sh} =8dB	2.94dB	0.166	0.716

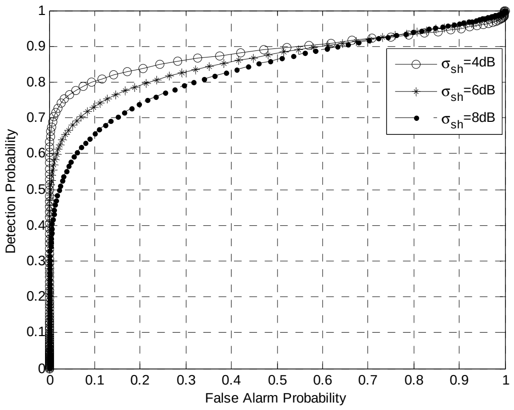

Figure 3. Detection and false alarm probability curve with different shadowing effects

Now let us study the overall performance of multi-antenna NLOS identification algorithm. Fig. 4 shows the miss-detection probability of the proposed and conventional algorithm under different K factor. The prior probability is set 0.5 and shadowing fade is set 8dB. It can be observed that the miss-detection probability gets the maximum around 0.5 when K factor is 2. This is because the decision threshold is 2.94dB (i.e. K equals 2) given shadowing fade at 8dB and the miss-detection probability is the maximum around threshold. Our algorithm could achieve lower miss-detection probability due to its better K factor estimation performance, which also has a robust identification result when the antenna configuration and scattering environment changes.

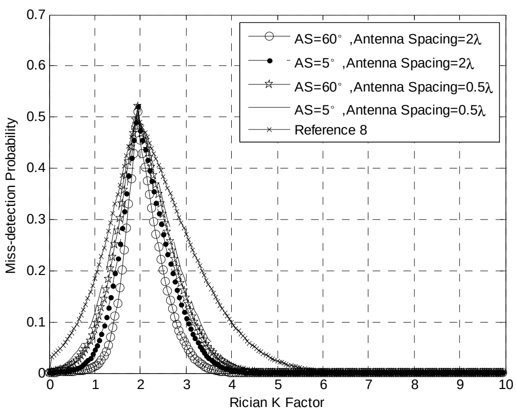

Figure 4. Miss-detection probability of the proposed algorithm and conventional metric

VI. Conclusion

This work proposes a metric called multi-antenna NLOS identification algorithm for MIMO-OFDM systems based on hypothesis test. It is observed that the different distributions of rician K factor under LOS and NLOS conditions can be used to identify signal propagation status. Simulation results confirm that combining multi-antenna K estimator and hypothesis test could achieve better NLOS identification performance compared to conventional metrics. The proposed algorithm could be a good candidate for NLOS identification for MIMO-OFDM based position localization systems.

References

[1] Cheng-Tse Chiang, Po-Hsuan Tseng, "Kai-Ten Feng. Hybrid Unified Kalman Tracking Algorithms for Heterogeneous Wireless Location Systems," IEEE Transactions on Vehicular Technology, vol. 61, no. 2, pp. 702-715, 2012.

[2] Kegen Yu, Ian Sharp, Y. Jay Guo. Ground-Based Wireless Positioning, New York: John Wiley & Sons, pp. 297-301, 2009.

[3] Zhonghai Wang, Zekavat Seyed A. "Omnidirectional Mobile NLOS Identification and Localization via Multiple Cooperative Nodes," IEEE Transactions on Mobile Computing, vol. 11, no. 12, pp. 2047-2059, 2012.

[4] Tsalolikhin E., Bilik I., Blaunstein N.. "A Single-Base-Station Localization Approach Using a Statistical Model of the NLOS Propagation Conditions in Urban Terrain," IEEE Transactions on Vehicular Technology, vol. 60, no. 3, pp. 1124-1137, 2011.

[5] N. Alsindi, M. Heidari, and K. Pahlavan. "Blockage identification in indoor UWB ranging using multi band OFDM signals," Wireless Communications and Networking Conference, Las Vegas, pp. 3231–3236, 2008.

[6] Genming Ding, Zhenhui Tan, Lingwen Zhang, "Hybrid TOA/AOA Cooperative Localization in Non-Line-of-Sight Environments," Vehicular Technology Conference (VTC Spring), Yokohama, Japan, pp. 1-5, 2012.

[7] Maali A., Mimoun H., Baudoin G., "A new low complexity NLOS identification approach based on UWB energy detection," Radio and Wireless Symposium, Phoenix, pp. 675-678, 2009.

[8] Doukas A., Kalivas G., "Rician K Factor Estimation for Wireless Communication Systems," International Conference on Wireless and Mobile Communications, Bucharest, pp. 69, 2009.

[9] C. Tepedelenlioglu, A. Abdi, G. B. Giannakis, "The Ricean K-Factor: estimation and performance analysis," IEEE Transactions on Wireless Communications, vol. 2, no. 4, pp. 799–810, 2003.

[10] Sun Jun and Yuan Dong-feng, "The Research on the Space Correlation in MIMO Systems," Journal of Electronics & Information Technology, vol. 30, no. 11,pp. 2580-2583, 2008

[11] M. Bakkali, A. Stephenne, and S. Affes, "Generalized moment-based method for SNR estimation," IEEE Wireless Communications and Net-working Conference, Hong Kong, pp. 2226-2230, 2007

[12] Ambawade Dayanand, Karia Deepak, Potdar Tejas, "Statistical Tuning of Walfisch-Ikegami Model in Urban and Suburban Environments," Fourth Asia International Conference on AMS, Kota Kinabalu, Malaysia,pp. 538-543, 2010

[13] W. Joseph, L. Martens, D. Plets, L. Verloock, "Extensive penetration loss measurements and models for different building types for DVB-H in the UHF band," IEEE Transactions on Broadcasting, vol. 55,no. 2, pp. 213-222, 2009.