This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the WCNC 2008 proceedings.

Performance of a New Low-Complexity Angular Spread Estimator in the Presence of Line-Of-Sight

Inès Bousnina[1], Alex Stéphenne[2,3], Sofiène Affes[3] and Abdelaziz Samet[1]
[1]Tunisia Polytechnic School B.P. 743 - 2078 La Marsa Tunisia
[2]Ericsson Canada, 8400, Decarie Blvd, Montreal, H4P 2N2, Qc, Canada
[3]INRS-ÉMT, 800, de la Gauchetière Ouest, Bureau 6900, Montréal, H5A 1K6, Qc, Canada
Emails: ines.bousnina@ept.rnu.tn,stephenne@ieee.org,affes@emt.inrs.ca,abdelaziz.samet@ept.rnu.tn

***Abstract*—This paper focuses on the problem of angular spread (AS) estimation at the base station in a macro-cellular system when a Line-Of-Sight (LOS) component is potentially present. We will limit our study to low-complexity methods prone to practical implementation. The paper demonstrates the limitations of the well-known low complexity AS estimation method, Spread Root-MUSIC. As supported by simulations, it introduces a lower complexity "Look-Up Table" (LUT) based approach that compares advantageously with Spread Root-MUSIC from the point of view of complexity and performance.**

I. Introduction

There exist several smart antenna techniques such as beamforming, antenna diversity and spatial multiplexing. Future smart antenna structures will switch from one technique to another according to the channel parameters [1]. One of the most important parameters is the multipath AS.

In the last two decades, many estimators have been developed to estimate the mean Angle of Arrival (AoA) and AS. Maximum Likelihood [4] and covariance matching [2] estimators are considered the most robust ones and give consistent estimates. But they also require high dimensional non-linear optimization. This is why lower complexity estimators such as Spread Root-MUSIC have been developed. The latter treats the non-LOS with small AS scenarios and is still quite complex.

We present here a new low complexity AS estimator in the presence of a LOS. First, our algorithm estimates the LOS component, i.e. the Rician factor K and the AoA of the LOS. The first parameter is estimated using the second and fourth order moments of the received signal. The method then deduces the correlation coefficient of the diffuse component. Then LUTs that express the AS and mean AoA as a function of the correlation coefficients of the diffuse component are used.

The paper is organized as follows. In the next section, the data model is presented and Spread Root-MUSIC is described. In the third section, we expose the new AS estimator in the presence of a LOS. In the fourth section, we study the performance of the new algorithm compared to Spread Root-MUSIC adapted to the presence of a LOS.

II. Data Model and Background

A. Data model

In our model, we consider the following assumptions:

1) Only the uplink (mobile to base station) transmission is considered.
2) The mobile has a single isotropic antenna surrounded by scatterers. The base station is located high enough not to be shadowed by local scatterers.
3) The SIMO (Single Input Multiple Output) model is considered.
4) The base station and the mobile are far enough from one another so as to create a near planar wavefront over the antenna-array surface.
5) The channel is composed of an infinite number of multipaths, continuously distributed in time (delay of arrival) and space.

We consider the estimation of the AS and the mean AoA from estimates over time of the time-varying channel coefficients associated with a single time-differentiable path at the multiple elements of an antenna array. Our model can therefore be associated with a narrowband channel, or with a given time-differentiable path of a wideband channel. Of course, in a wideband channel scenario, the potential presence of a LOS would only be considered for the first time-differentiable path, and knowledge of a zero K-factor could be assumed for the rest of the paths.

In our model we consider the following expression of the Rician channel coefficient at antenna element[1] k [5]:

$$\begin{aligned} x_k(t) &= \sqrt{\tfrac{\Omega}{K+1}} a_k(t) \\ &+ \sqrt{\tfrac{K\Omega}{K+1}} exp\left(j2\pi F_d \cos(\gamma)t + j2\pi d_{0k}\sin(\theta_{0k})\right), \end{aligned} \quad (1)$$

where a_k is the channel coefficient of the diffuse component (Rayleigh channel), Ω is the power of the received signal, K is the Rician K-factor, F_d and γ are, respectively, the Doppler frequency and Doppler angle. d_{0k} is the distance between the antenna reference 0 and the antenna element k and θ_{0k} is the AoA of the LOS, as shown in Fig. 1. Indeed, in our model we consider a symmetry in the scatterers where the mean AoA corresponds to the AoA of the LOS.

[1]The described model is valid for 2-D arbitrary arrays.

1525-3511/08/$25.00 ©2008 IEEE

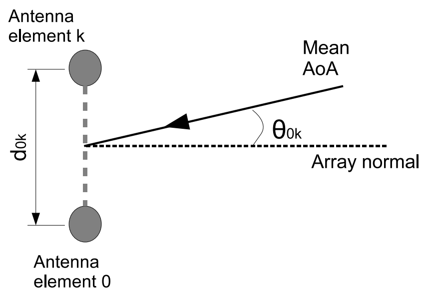


Fig. 1. Two antenna elements of an antenna array at the base station.

Let X_k be:

$$X_k = [x_k(0) \cdots x_k(N-1)]. \tag{2}$$

The correlation coefficient of the Rician channel coefficients is:

$$R_{T_{kl}} = \frac{E[X_k X_l^H]}{\sqrt{E[|X_k|^2]E[|X_l|^2]}}, \tag{3}$$

where $(.)^H$ is the transconjugate operator.

So the correlation matrix would be:

$$R_T = \frac{1}{K+1} \underbrace{R}_{\text{Diffuse comp.}} + \frac{K}{K+1} \underbrace{e^{j2\pi M}}_{\text{LOS comp.}}, \tag{4}$$

where M is a square matrix defined by: $M_{kl} = d_{0k}\sin(\theta_{0k}) - d_{0l}\sin(\theta_{0l})$ and R is the correlation matrix of the diffuse component (Rayleigh model) defined by:

$$R_{kl} = \int_{\theta_m-\pi}^{\theta_m+\pi} f(\theta,\theta_{kl},\sigma) exp\Big(-j2\pi d_{kl}\frac{f_c}{c}\sin\theta\Big)d\theta, \tag{5}$$

where the function, $f(\theta,\theta_{kl},\sigma_{kl})$ is the power density function with respect to the azimuth angle of arrival θ. θ_{kl} is the mean AoA or nominal direction of arrival and σ is the angular spread or the standard deviation of the angular distribution. f_c is the carrier frequency, c is the speed of light and d_{kl} is the inter-element spacing.

If we consider the diffuse component and we assume small AS ($\sigma < \sigma_{threshold}$), the correlation coefficient R would be:

- *For a Gaussian distribution*

$$R_{kl} \approx \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} exp\left(\frac{-(\theta-\theta_{kl})^2}{2\sigma^2} - j\frac{2\pi}{\lambda}d_{kl}\sin\theta\right)d\theta. \tag{6}$$

With small standard deviation σ, $\sin\theta$ can be linearized around θ_m (mean of θ_{kl}) in the following way: $\sin\theta = \sin\theta_m + (\theta-\theta_m)\cos\theta_m$, yielding:

$$R_{kl} \approx exp\left(-2\pi^2\sigma^2\frac{d_{kl}^2}{\lambda^2}\cos^2\theta_{kl}\right) exp\left(-j2\pi\frac{d_{kl}}{\lambda}\sin\theta_{kl}\right). \tag{7}$$

- *For a Laplacian distribution*

$$R_{kl} \approx \frac{1}{1+2\pi^2\sigma^2\frac{d_{kl}^2}{\lambda^2}\cos^2\theta_{kl}} exp\left(-j2\pi\frac{d_{kl}}{\lambda}\sin\theta_{kl}\right). \tag{8}$$

In this paper, we consider only Gaussian and Laplacian angular distributions, the most popular ones in the literature. But our approach is still valid for other angular distributions.

B. Spread Root-MUSIC

Spread Root-MUSIC [3] is a derivative of the Root-MUSIC algorithm. We consider $\hat{R}_c$, the estimated covariance matrix with: $\hat{R}_{c_{kl}} = \frac{1}{N}\sum_{n=0}^{N-1} x_k(n)x_l^H(n)$. The Spread Root-MUSIC algorithm is then:

$$\{\hat{\nu}_1, \hat{\nu}_2\} = Root - MUSIC(\hat{R}_c, nb.sources = 2) \tag{9}$$

$$\hat{\omega} = \frac{\hat{\nu}_1 + \hat{\nu}_2}{2} \tag{10}$$

$$\hat{\sigma}_\omega = \lambda_K^{-1}\left(\frac{|\hat{\nu}_1 - \hat{\nu}_2|}{2}\right) \tag{11}$$

$$\hat{\theta}_m = arcsin\left(\frac{\hat{\omega}}{2\pi\Delta}\right) \tag{12}$$

$$\hat{\sigma}_R = \frac{\hat{\sigma}_\omega}{2\pi d\cos\hat{\theta}_m} \tag{13}$$

where $\hat{\sigma}_R$ is the AS of the Rician fading channel and λ_K is the function defined by:

$$\{\lambda_K(\sigma_\omega), -\lambda_K(\sigma_\omega)\} = Root{-}MUSIC\left(R_c(\theta_m = 0, K), 2\right). \tag{14}$$

Indeed, when the angular distribution is symmetrical around the mean AoA $\theta_m = 0$, and one uses Root-MUSIC with a "two point sources" assumption, Root-MUSIC gives a pair of estimates symmetrically placed on both sides of the array normal. There is no closed-form expression for the function λ_K. But it can be precalculated and the inverse function is easily interpolated from the tabulated values. Since the covariance depends on the factor K, we need a LUT for each value of K as shown in Fig. 2. In our simulations, a LUT was computed for every value of K with a resolution of 0.1.

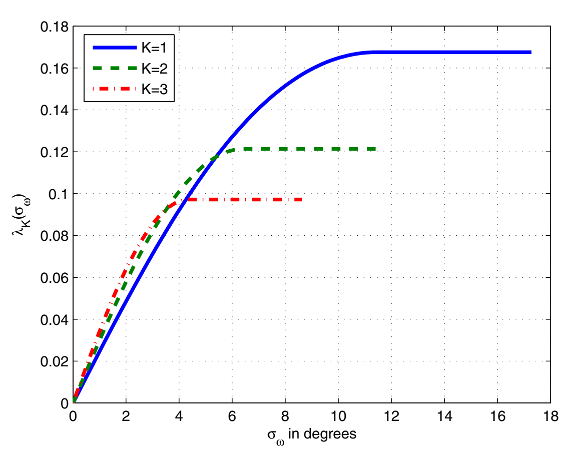


Fig. 2. Function λ_K of Root-MUSIC for a 7-element ULA and a normally distributed AS.

As you can notice, Spread Root-MUSIC can not estimate an AS higher than a certain limit. The maximum amplitude of the AS parameter that can be estimated decreases as the K-factor increases. In practice, Spread Root-MUSIC requires the K-factor estimate and the *a priori* knowledge of the angular distribution of the received signal to select the appropriate LUT.

III. New Angular Spread Estimator

Our approach is to estimate the LOS part of the correlation coefficient R_T. Then the diffuse part R is deduced and the AS is extracted from LUT. The latter expresses the desired parameter as a function of the magnitude and the phase of the correlation coefficient R. One can argue that the same principle can be applied for the case of a Rician channel. In other terms, the AS is directly estimated by means of LUT expressing the AS as a function of the correlation coefficient (4). In this case, a huge number of LUTs is needed, one for each angular distribution and each factor K. Besides, we are not sure to find a one-to-one transformation that associates one correlation coefficient to a unique AS. This is why our approach is to estimate the LOS part of the correlation coefficient and remove it, to use the same LUT as in the non-LOS case. In this section, we first estimate the LOS part. Then the AS estimation from the diffuse component R is described.

A. LOS and diffuse component estimation

As described in (4), the LOS part depends on the AoA of the LOS which is associated to the mean AoA as:

$$\hat{\theta}_{kl} = arcsin(\frac{-\angle \hat{R}_{T_{kl}}}{2\pi \frac{d_{kl}}{\lambda}}), \tag{15}$$

where $\{(k,l)\}$ are such that $d_{kl} \approx \frac{\lambda}{2}$. The final mean AoA estimate $\hat{\theta}_m$ is the mean of $\hat{\theta}_{kl}$ over all antenna elements pairs.

To determine the LOS component, we also need to estimate the Rician K-factor. Many K-factor estimators have been developed. In [7], the K estimator is based on statistics of the instantaneous frequency (IF) of the received signal. In [8], Maximum Likelihood estimators that only use samples of both the fading envelope and the fading phase are derived. In [9], a general class of moment-based estimators which use the signal envelope is proposed. A K estimator that relies on the in-phase and quadrature phase (K_{IQ}) components of the received signal is introduced there as well.

We choose to use the closed-form presented in [9] which is easily implemented. This estimator uses the second and fourth order moments of the received signal to estimate K:

$$K_{24} = \frac{-2\mu_2^2 + \mu_4 - \mu_2\sqrt{2\mu_2^2 - \mu_4}}{\mu_2^2 - \mu_4}, \tag{16}$$

where $\mu_2 = E[|X|^2]$ and $\mu_4 = E[|X|^4]$ are, respectively, the second-order and fourth-order moments of the received signal. The K_{24} estimator presents high RMSE when the factor K is important. In practice, only channel coefficient estimates are available to compute the moments, so that a noise term must be added to (1). We denote by SNR the signal-to-noise ratio of the channel coefficient estimates. To reduce the noise effect, we consider that a SNR estimate is available, and we use the following expressions of the moments estimates at antenna element l:

$$\hat{\mu}_2^{(l)} = \frac{1}{N}\sum_{n=0}^{N-1} |x_l(n)|^2 \left(\frac{S\hat{N}R}{S\hat{N}R+1}\right), \tag{17}$$

and

$$\hat{\mu}_4^{(l)} = \frac{1}{N}\sum_{n=0}^{N-1} |x_l(n)|^4 \frac{\hat{k}_a S\hat{N}R^2}{\hat{k}_a S\hat{N}R^2 + 4S\hat{N}R + 2}, \tag{18}$$

where $\hat{k}_a$ is the estimated kurtosis of the Rician channel and is computed as follows:

$$\hat{k}_a^{(l)} = \frac{(S\hat{N}R+1)^2 \frac{\sum_{n=0}^{N-1}|x_l(n)|^4}{\left(\sum_{n=0}^{N-1}|x_l(n)|^2\right)^2} - 4S\hat{N}R - 2}{S\hat{N}R^2}. \tag{19}$$

We consider then a SNR estimate ($S\hat{N}R$) with a Gaussian error estimation:

$$S\hat{N}R(dB) = SNR(dB) + \epsilon, \tag{20}$$

where ϵ is normally distributed with zero mean, i.e. $N(0, \sigma_\epsilon^2)$. Since SNR estimators can often operate over long durations, they exhibit low power estimation errors. Therefore, we choose $\sigma_\epsilon^2 = 0, 1$ and 2.

The final K-factor estimate is the mean of $\hat{K}_{24}^{(l)}$ over all antenna elements l. With those estimates of the second and fourth-order moments of the received signal, as shown in Fig. 3, we obtain lower Normalized Root Mean Square Error (NRMSE) for the K_{24} estimator.

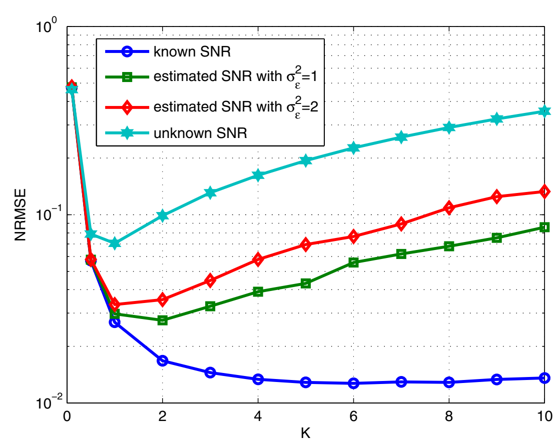


Fig. 3. NRMSE in K estimation.

Since we consider a SNR estimate for the computation of the moments of the received signal, we do the same for the correlation coefficient. The estimated correlation coefficient (for $k \neq l$) of the Rician fading is :

$$\hat{R}_{T_{kl}} = \frac{\sum_{n=0}^{N-1} x_k(n) x_l^H(n)}{\sqrt{\sum_{n=0}^{N-1} |x_k(n)|^2 \sum_{n=0}^{N-1} |x_l(n)|^2 \left(\frac{S\hat{N}R}{S\hat{N}R+1}\right)}}. \quad (21)$$

Once the factor K and the AoA of the LOS are estimated, we deduce the correlation coefficient R:

$$\hat{R} = (\hat{K}+1)\left(\hat{R}_T - \frac{\hat{K}}{\hat{K}+1}\ exp(j2\pi\hat{M})\right). \quad (22)$$

B. AS estimation in a LOS scenario

The idea is to find a one-to-one transformation that expresses the AS as a function of the correlation matrix R. As you can notice, it is difficult to extract a simple one-to-one transformation. But if we assume small AS ($\sigma < \sigma_{threshold}$), simple closed-forms can be deduced from (7) and (8). The final expressions for the AS would be:

- *Gaussian distribution*

$$\sigma \approx \frac{\sqrt{-2ln|R_{kl}|}}{2\pi\frac{d_{kl}}{\lambda}\cos\theta_{kl}}. \quad (23)$$

- *Laplacian distribution*

$$\sigma \approx \frac{\sqrt{\frac{2}{|R_{kl}|} - 2}}{2\pi\frac{d_{kl}}{\lambda}\cos\theta_{kl}}. \quad (24)$$

In the presence of larger AS, there is no one-to-one transformation that determines the AS from the correlation coefficients of the diffuse component only. But if one knows *a priori* the angular distribution type (Gaussian, Laplacian, etc.) and ensures that the AS and mean AoA vary in predefined ranges, such transformation exists[2]. For example, for the Gaussian distribution the mean AoA could vary in [-90,90] degrees while the AS should be inferior to 55 degrees. Since the AS is typically lower than ten degrees [11], both conditions are satisfied in a macro-cellular system that uses 3 sectors. For each distribution type, a LUT can therefore be computed off-line. The LUT expresses the AS and mean AoA as a function of the magnitude and phase of the correlation coefficient R.

Analysis of (23) and (24) shows that when the amplitude of the correlation coefficient is close to one or zero, the impact of a correlation coefficient amplitude estimation error on AS estimation increases. To overcome this limitation, we consider distant antenna elements while at the same time making sure to only use a correlation coefficient with magnitude not close to zero (say higher than 0.05). Since our purpose is to exploit a correlation coefficient magnitude not close to one, we consider inter-elements spacing $d_{kl} > \lambda$. This does not imply that we consider all elements spaced by distance higher than λ. In fact, the chosen distant pairs depend on the array itself. If the array presents several elements (say more than 10), we choose the pairs distant by at least 3λ. But when the array is composed by few elements (say 5), in this case we choose the ones spaced by $d_{kl} > \lambda$. So the procedure would be as follows. We first consider the closest pairs, with inter-element spacing $d \approx \frac{\lambda}{2}$. For each pair, from the LUT and the estimated correlation coefficient of the diffuse component, we extract the associated AS ($\tilde{\sigma}_{kl}^{(c)}$). Then, a preliminary AS estimate ($\tilde{\sigma}^{(c)} = mean(\tilde{\sigma}_{kl}^{(c)})$) is obtained. If the preliminary AS is higher than a certain threshold which depends on the angular distribution and the factor K, the final AS estimation is $\hat{\sigma} = \tilde{\sigma}^{(c)}$. Otherwise, the algorithm considers the correlation coefficient associated with distant elements pairs. As mentioned before, correlation coefficients with module higher than 0.05 are used to obtain AS estimates $\tilde{\sigma}_{kl}^{(d)}$ thanks to the closed-forms (23) and (24). So the final AS estimation would be the mean of the $\tilde{\sigma}_{kl}^{(d)}$. The total AS of the Rician fading channel would be:

$$\hat{\sigma}_R = \frac{\hat{\sigma}}{\hat{K}+1}. \quad (25)$$

[2]The one-to-one transformation is possible, when the inter-elements distance is small ($d \simeq \frac{\lambda}{2}$).

Fig. 4 provides a summary of the new AS estimator in the presence of a LOS.

$\hat{K} = \frac{-2\mu_2^2+\mu_4-\mu_2\sqrt{2\mu_2^2-\mu_4}}{\mu_2^2-\mu_4}$

$\hat{\theta}_{kl} = arcsin(\frac{-\angle\hat{R}_{T_{kl}}}{2\pi\frac{d_{kl}}{\lambda}})$

$\hat{\theta}_m = mean(\hat{\theta}_{kl})$

$R = (\hat{K}+1)\left(R_T - \frac{\hat{K}}{\hat{K}+1}\ exp(j2\pi\hat{M})\right)$

$D_{kl} = \begin{cases} 1 & \text{if } d_{kl} \approx \frac{\lambda}{2} \\ 0 & \text{otherwise} \end{cases}$

$B_{kl} = \begin{cases} 1 & \text{if } d_{kl} > \lambda \\ 0 & \text{otherwise} \end{cases}$

$R_{kl}^{(c)} = R_{kl}D_{kl}$

$R_{kl}^{(d)} = R_{kl}B_{kl}$

$\left[\tilde{\sigma}_{kl}^{(c)}, \hat{\theta}_{kl}\right] = LUT(|R_{kl}^d|, \theta_{R_{kl}^{(c)}})$

$\tilde{\sigma}^{(c)} = mean(\{\tilde{\sigma}_{kl}^{(c)}\})$

$E = \{(k,l)/|R_{kl}^{(d)}| > 0.05\}$

If $cardinal(E) < 1$ & $\tilde{\sigma}^{(c)} > \sigma_{threshold}$

$\quad \hat{\sigma} = \tilde{\sigma}^{(c)}$

Else

$\quad \tilde{\sigma}_{kl}^{(d)} = g(\hat{\theta}_m, |R_{kl}^{(d)}|)/(k,l) \in E$

The function g refers to (23) or (24)

$\quad \hat{\sigma} = mean(\{\tilde{\sigma}_{kl}^{(d)}\})$

End

$\hat{\sigma}_R = \frac{\hat{\sigma}}{\hat{K}+1}$

Fig. 4. New estimator algorithm in the presence of a LOS.

IV. NUMERICAL RESULTS

To study the performance of the new estimator, we compare it with Spread Root-MUSIC [3], which is the natural choice for our comparative study because it is the most well-known approach with relatively low complexity. We illustrate the performance of the new AS estimator by means of Monte-Carlo simulations. We consider the ULA configuration with 7 elements and inter-elements spacing $d = \frac{\lambda}{2}$.

We assume here that the channel coefficients are obtained through an appropriate channel estimation algorithm, and that the resulting time-varying channel coefficient estimates can be adequately modeled by the sum of the true time-varying channel coefficients with additive white Gaussian noise (AWGN). The accuracy of the channel estimation procedure is then controlled by the variance of the AWGN component. In our simulations, for the diffuse component, we used a non-selective frequency (flat) Rayleigh channel. We also considered the Rayleigh channel simulator described in [6]. The azimuth angular spread distribution for the incoming multipath signals will be of Gaussian or Laplacian type. The carrier frequency was set to 1.9 GHz, which results in a wavelength λ of 15.79 cm. The mobile speed was set to about 80 Km/h (22.2 m/s), which results in a Doppler frequency f_d of 140.74 Hz. The sampling interval was set to $T_s = \frac{1}{1500}ms$. The SNR of the estimated channel coefficients is 15 dB.

To study the effect of the $\hat{K}_{24}$ estimation error and the variance σ_ϵ^2 of the estimated $S\hat{N}R$ on the AS estimation, we consider several scenarios, illustrated in Fig. 5 (a,b). In the first one, we assume the *a priori* knowledge of the K-factor, i.e. we use the true value of K to estimate the diffuse component. In the second case, we consider the true value of the SNR. In the last two cases, an estimated $S\hat{N}R$ with variance $\sigma_\epsilon^2 = 1, 2$ is used. As one can notice in Fig. 5 (b), the AS NRMSE obtained with Spread Root-MUSIC for relatively small true AS values (3 degrees here) can be smaller when the SNR is assumed unknown than when the SNR is known or estimated. This behavior is only visible for small AS values and is due to the resulting K estimates having high NRMSE when the SNR is assumed unknown, which translates into the frequent use of rapidly saturating λ_K functions (see fig. 2.), and therefore frequently selected artificially low AS estimates. These artificially low AS estimates turn out to be beneficial from the AS NRMSE point of view when the AS is indeed small. When we vary the AS for a fixed K-factor ($K = 3$, $\theta_m = -10^o$), the NRMSE given by the new estimator decreases when the AS increases. As shown in Fig. 7, the new estimator gives lower NRMSE than Spread Root-MUSIC for high AS ($\sigma > 3$).

As shown in Fig. 6, for the mean AoA estimation, our estimator presents better estimates in all tested scenarios (different AS and mean AoA). Concerning the AS estimation, whether we assume the *a priori* knowledge of the SNR or use an estimate with variance $\sigma_\epsilon^2 = 1, 2$, the new estimator offers close estimates to the case when we consider the true value of K. As expected, in the case of unknown SNR, the new estimator presents high NRMSE. As mentioned before, this is due to the important estimation error exhibited by the K_{24} estimator. For Spread Root-MUSIC, the K-factor estimation does not affect much the performance of Spread Root-MUSIC. In Fig. 5 (c,d), we compare both estimators. For large AS, the new estimator offers lower NRMSE than Spread Root-MUSIC. But for small AS, our estimator presents slightly higher NRMSE. Still, while Spread Root-MUSIC requires the eigen-decomposition of the covariance matrix and finding the roots of a polynomial, our method uses only a LUT, simple closed-forms and some logical operations. Moreover, due to the definition itself of the function λ_K [3], Spread Root-MUSIC can not estimate an AS greater than a certain limit. Indeed, for a large AS Spread Root-MUSIC shows high NRMSE.

V. Conclusion and Discussion

In this paper, we presented a new low-complexity AS estimator in Rician fading. The new method estimates the AS by estimating the correlation coefficient of the diffuse component then uses LUT to extract the desired parameters. To decrease the impact of the factor K estimation error on the AS estimation, we normalized the correlation coefficient and the moments of the received signal by using an estimated SNR. We compared the new method with Spread Root-MUSIC. Simulations showed that the new technique gives lower NRMSE in the presence of large AS while being of lower computational complexity. These results are obtained whith the *a priori* knowledge of the angular distribution of the received signal. Presently, we are working on extending the new method to cases for which the type of angular distribution is unknown.

References

[1] K. Miyoshi and M. Uesugi, "*Radio Base Station Unit and Radio Communication Method*," US Patent Application Publication no. US 2002/0123371 A1, Sept. 5 2002.

[2] B. Ottersten, P. Stoica and R, Roy, "*Covariance Matching Estimation Techniques for Array Signal Processing,*" *Digital Signal Processing*, 8(3): 185-210, Jul. 1998.

[3] M. Bengtsson and B. Ottersten, "*Low Complexity Estimators for Distributed Sources*," *IEEE Transactions Signal Processing*, vol. 48, no. 8, pp. 2185-2194, Aug. 2000.

[4] T. Trump and B. Ottersten, "*Estimation of Nominal Directions of Arrival and Angular Spread Using an Array of Sensors*," *Signal Processing*, vol.50, no.12, pp.57-69, Apr. 1996.

[5] A. Abdi and M. Kaveh, "*A SpaceTime Correlation Model for Multielement Antenna Systems in Mobile Fading Channels*," *IEEE Journal On Selected Areas In Communications*, vol. 20, no. 3, Apr. 2002.

[6] A. Stéphenne and B. Champagne, "*Effective Multi-Path Vector Channel Simulator for Antenna Array Systems*", *IEEE Transactions On Vehicular Technology*, vol. 49, no. 6, pp. 2370-2381, Nov. 2000.

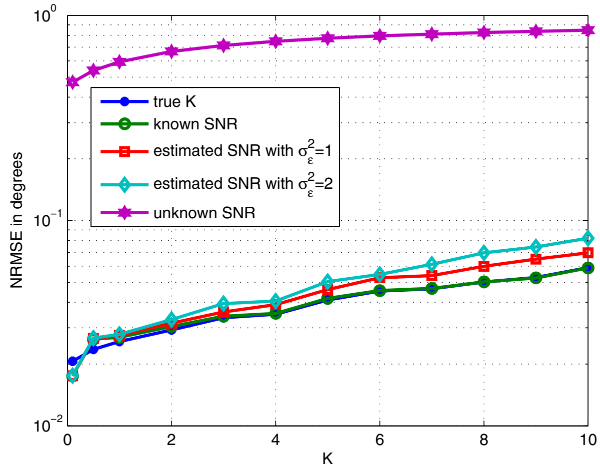
[7] G. Azemi, B. Senadji, and B. Boashash, "*Ricean K-Factor Estimation in Mobile Communication Systems*," *IEEE Communications Letters*, vol. 8, no. 10, pp. 550-560, Oct. 2004.

[8] Y. Chen, N. C. Beaulieu, "*Maximum Likelihood Estimation of the K Factor in Ricean Fading Channels*", *IEEE Communications Letters,* vol. 9, no. 12, pp.1040-1042, Dec. 2005.

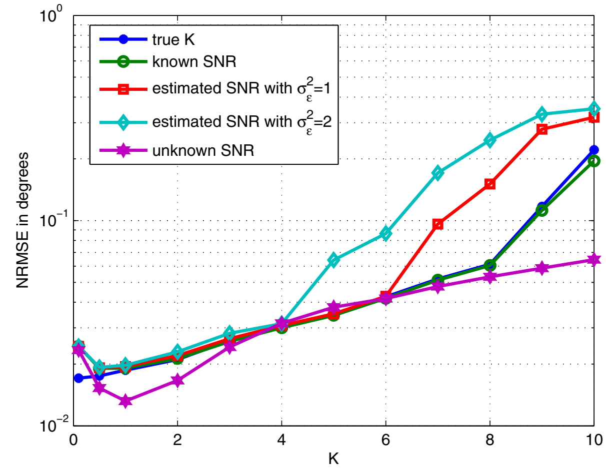
[9] C. Tepedelenlioglu, A. Abdi, and G. B. Giannakis, "*The Ricean K Factor: Estimation and Performance Analysis*", *IEEE Transactions On Wireless Communications,* vol. 2, no. 4, pp. 799-810, Jul. 2003.

[10] H. Xu, G. Wei and J. Zhu, "*A Novel SNR Estimation Algorithm for OFDM,*", *Vehicular Technology Conference*, vol.5, pp. 3068-3071, Jun. 2005.

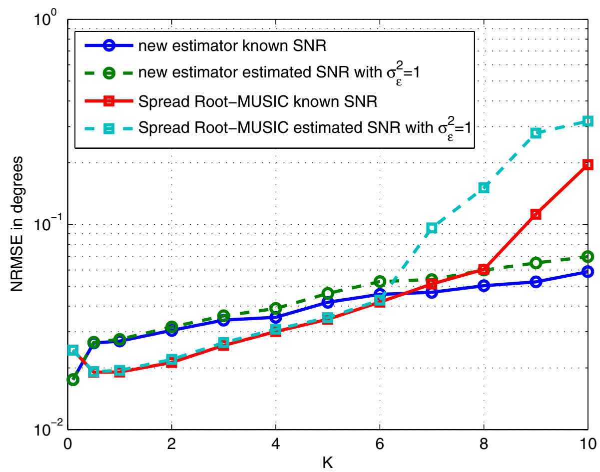
[11] B. Ottersten, "*Array processing for wireless communication,*" in *Proceedings of the 8th IEEE Signal Processing Workshop on Statistical Signal and Array Processing* , pp. 466-473, Jul. 1996.



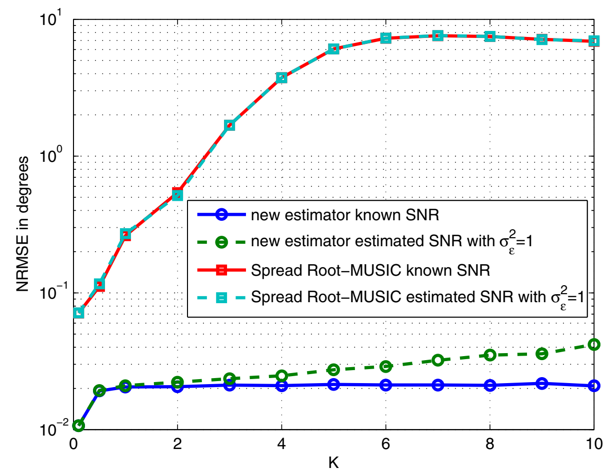
(a) NRMSE in σ_R ('Gaussian', $\sigma = 3^o$, $\theta_m = -10^o$)
New estimator



(b) NRMSE in σ_R ('Gaussian', $\sigma = 3^o$, $\theta_m = -10^o$)
Spread Root-MUSIC

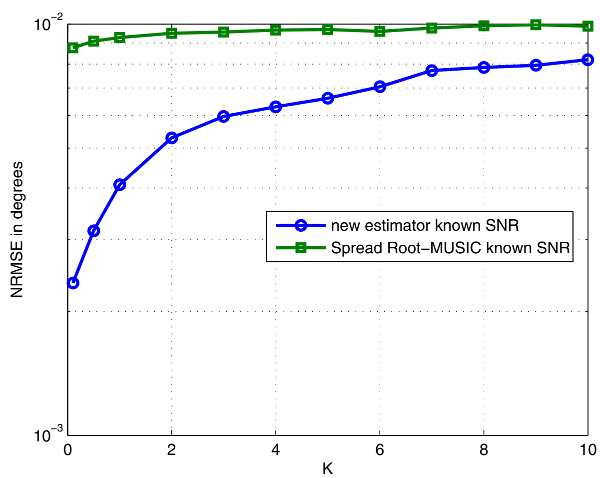


(c) NRMSE in σ_R ('Gaussian', $\sigma = 3^o$, $\theta_m = -10^o$)



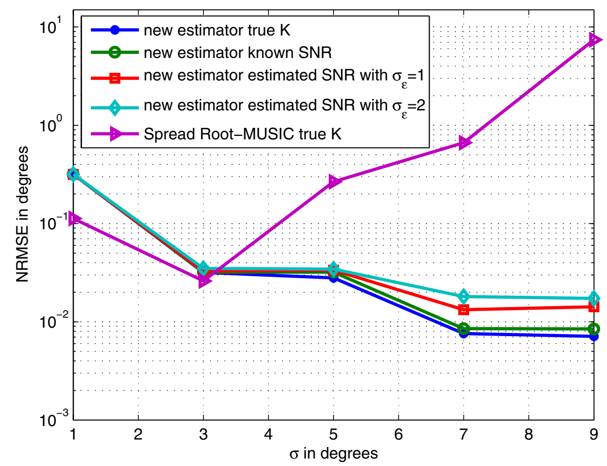
(d) NRMSE in σ_R ('Laplacian', $\sigma = 7^o$, $\theta_m = -20^o$)

Fig. 5. NRMSE in AS estimates of the Rician fading channel.



NRMSE in θ_m ('Laplacian', $\sigma = 7^o$, $\theta_m = -20^o$)

Fig. 6. NRMSE in AoA estimates of the Rician fading channel.



NRMSE in σ_R ('Gaussian', $\theta_m = -10^o$, $K = 3$)

Fig. 7. NRMSE in AS estimates of the Rician fading channel.