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Estimation of Rician K-Factor in the Presence of Nakagami-m Shadowing for the LoS Component

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***Abstract*—The received signal in Rician multipath channels is modeled as a complex constant, accounting for the main (LoS) path, added to a circular complex Gaussian random variable, modeling all the diffusive secondary paths. The Rician K-factor is accordingly defined as the ratio between the powers of LoS and diffusive components. Under this (widely assumed) multipath model, a closed-form expression for the Rician K-factor estimate is commonly obtained exploiting the second and fourth moments of the received signal amplitude. However, in mobile communications, random shadowing effects make the LoS component fluctuating (Rician shadowed model) leading to a performance degradation of the conventional estimator. With focus on land mobile satellite communications, in this letter, a novel estimation procedure of the Rician K-factor, aimed at avoiding the bias error of the conventional estimator when the LoS component is Nakagami-m distributed, is proposed and assessed. Specifically, the estimate is computed using the solution of a system of three equations and three unknowns in conjunction with the likelihood function of the received signal. The performance analysis shows that the new estimator can guarantee better performance than the conventional estimator.**

***Index Terms*—Rician K-factor, Rician Shadowed Model, Land Mobile Satellite Communications, Nakagami-m Shadowing, Multipath Models.**

I. INTRODUCTION

Rician (or Ricean) factor (also referred to as Rician/Ricean K-factor) is widely used to characterize multipath fading channels as the ratio between the power of the main path and the total power of diffusive secondary paths [1]–[4]. It is derived from the well-known Rice's model for the received samples, which can be written as[1] $r_l = a_l + n_l$, $l = 1, \ldots, L$, where $a_l = s_l e^{j\varphi_l}$, with $s_l > 0$ and $\varphi_l \in [0\ 2\pi]$, is a complex constant corresponding to the line-of-sight (LoS) path and $n_l \sim \mathcal{CN}(0, \sigma^2)$ accounts for a large number of secondary non-line-of-sight (NLoS) paths due to the reflected echoes[2]. Thus, the resulting distribution of the received sample amplitude is the Rice distribution. In the case where the main path does not exist (NLoS condition), namely $a_l = 0$, the Rice distribution reduces to the special case of Rayleigh. The Rician K-factor is widely used to discriminate between LoS versus NLoS wireless channels and represents a measure of the communication link quality [2]. As a consequence, it becomes of practical importance in several scenarios, since it allows to undertake suitable countermeasures against the deleterious impact of the NLoS condition (e.g., adaptive modulation [6], geolocation applications [7], etc.). Assuming the validity of Rice's model, a common estimation procedure for the Rician K-factor exploits the second and fourth order moments of the received signal samples to obtain a closed-form expression for K-factor estimator as the solution of a system of two equations (the measured moments) with two unknowns (i.e., LoS and diffusive powers). The Rician factor is then estimated by the ratio between the numerical values of the two above unknowns [1]–[4], [7], [8]. Alternative (more time-demanding) estimators can be also obtained by means of iterative algorithms which use the first and second order moments [3]

However, in mobile communications, random fluctuations of the LoS component may occur due to the relative motion between transmitters and receivers. Specifically, when buildings, trees, hills, etc., yield complete or partial blockage of the LoS, its amplitude becomes a random variable (see, for instance, [9]). This phenomenon is referred to as LoS shadow fading and a well-known model for it has been introduced in [10], where the LoS component is assumed to follow the log-normal distribution. In spite of a good match to experimental data, this model leads to complicated expressions for the involved statistics. To overcome this limitation, in [11] a suitable approximation of the Loo's model has been proposed in the context of Land Mobile Satellite (LMS) communications. More precisely, the amplitude fluctuation of the LOS component is modeled in terms of a Nakagami-m distribution[3] in place of the log-normal distribution (see also [7], [12]–[15]).

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[1]In what follows, $\Re\{\cdot\}$ and $|\cdot|$ are the real part and the modulus of the complex argument, respectively. The acronym iid means independent and identically distributed while $E[\cdot]$ denotes statistical expectation. The gamma function is denoted by $\Gamma(m)$, whereas $\Phi(x, y; a) ={}_1 F_1(x; y; a)$ is the *Kummer Confluent Hypergeometric Function* [5]. We write $x \sim \mathcal{CN}(m, \sigma^2)$ if x is a circular complex normal random variable with mean m and variance $\sigma^2 > 0$; $x \sim \mathcal{U}(0, 2\pi)$ means that x obeys the uniform distribution within $[0,\ 2\pi]$; $x \sim$Nakagami$(m,\ \Omega)$ indicates that x is a Nakagami-m random variable with parameters m and Ω. Finally, $\mathbb{R}^+$ is the set of positive real numbers.

[2]Notice that the thermal noise generated by the electronic devices can be incorporated into n_l, whose power is the result of the superposition of thermal noise and NLoS paths. However, without loss of generality, we neglect this component since an estimate of its power level can be reasonably assumed available at the receiver and used to suitably estimate the NLoS power.

[3]It is worth underlining that Nakagami-m distribution encompasses several cases according to the values of its shape parameter m ($m < 1$ for Hoyt, $m = 1$ for Rayleigh, and $m \gg 1$ for Rice distributions).

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Note that Nakagami-m distribution stems from assuming that the power of the LoS component obeys the gamma distribution [11], [14]–[16]. More recently, this model has been exploited for device-to-device/underwater communications and in radar [17]–[19]

Now, it is important to highlight that the aforementioned estimation procedure of the K-factor has become very common in communications and is applied regardless the possible random fluctuation of the LoS component. The consequence may be a systematically erroneous (biased) value of the Rician factor estimate [7]. The reason is that the conventional algorithm allocates any signal variation to the diffusive component, although due to a randomly fluctuating LoS signal. Motivated by this lack and with focus on LMS communications, in this letter, we propose a new estimation procedure to avoid the bias error in case of LoS fluctuations, when the latter follows the Nakagami-m distribution. Thus, at the design stage, we assume that s_l ∼Nakagami(m, Ω), while $\varphi_l \sim \mathcal{U}(0, 2\pi)$. Then, the method of moments is exploited to come up with a system of three equations (i.e., the second, fourth, and sixth estimated statistical moments) and three unknowns (LoS and diffusive powers, as well as the shape parameter m). In the presence of a set of admissible solutions, the proposed procedure uses the joint likelihood function of the received samples to select the solution returning the maximum likelihood value. As a final remark, the proposed procedure can also be applied to the estimation of unknown parameters of Nakagami-m fading channels in the presence of thermal noise.

The remainder of this letter is organized as follows. In the next section, the estimation procedure is described in detail, whereas Section III provides some numerical examples. Finally, concluding remarks and hints for future work are given in Section IV.

II. Estimation Procedure

In the case of Rician shadowed channel where the LoS amplitude follows the Nakagami-m distribution with unknown shape and spread parameters $m > 0.5$ and $\Omega > 0$, respectively, the Rician factor can be expressed as $K = \frac{E[|a_l|^2]}{\sigma^2} = \frac{E[s_l^2]}{\sigma^2} = \frac{\Omega}{\sigma^2}$. It is clear that the estimates of Ω and σ are required to obtain a numerical value for K. To this end, we jointly exploit the method of moments and the probability density function (pdf) of the received data, which is used to sift the admissible solutions of a system of three equations as shown below.

Let us assume that a set of L iid observations, $R = \{r_1, \ldots, r_L\}$, is available at the receiver and that for the lth observation, $n_l \sim \mathcal{CN}(0, \sigma^2)$, $\varphi_l \sim \mathcal{U}(0, 2\pi)$, and s_l ∼Nakagami(m, Ω) are statistically independent. Since the r_ls are iid, in the following, we omit the subscripts for simplicity. Now, let $\hat{\mu}_2(R)$, $\hat{\mu}_4(R)$, and $\hat{\mu}_6(R)$ be consistent estimators of the noncentral moments of order 2, 4, and 6, respectively, obtained as functions of the collected data[4]. The analytical expressions of these moments can be obtained focusing on a single sample $r = se^{j\varphi} + n$ and observing that $|r| = \left|re^{-j\varphi}\right|$. Thus, the unknown statistical parameters of $|r|$ can be computed resorting to $|re^{-j\varphi}|$ as follows

$$\begin{cases} E[|r|^2] = E[|re^{-j\varphi}|^2] = \Omega + \sigma^2, \\ E[|r|^4] = E[|re^{-j\varphi}|^4] = 2\sigma^4 + 4\sigma^2\Omega + m_1\Omega^2, \\ E[|r|^6] = E[|re^{-j\varphi}|^6] = 6\sigma^6 + 9\sigma^2 m_1\Omega^2 + \Omega^3 m_2 + 18\Omega\sigma^4, \end{cases} \tag{1}$$

where $m_1 = \frac{m+1}{m}$ and $m_2 = \frac{(m+2)(m+1)}{m^2}$. Finally, the system of equations for parameter estimation is given by

$$\begin{cases} \hat{\mu}_2 = \Omega + \sigma^2, \\ \hat{\mu}_4 = 2\sigma^4 + 4\sigma^2\Omega + \frac{m+1}{m}\Omega^2, \\ \hat{\mu}_6 = 6\sigma^6 + 9\sigma^2\frac{m+1}{m}\Omega^2 + \Omega^3\frac{(m+2)(m+1)}{m^2} + 18\Omega\sigma^4, \end{cases} \tag{2}$$

where $\hat{\mu}_2$, $\hat{\mu}_4$, and $\hat{\mu}_6$ are realizations of the estimators. In order to solve this system, let $x_1 = \Omega$, $x_2 = \sigma^2$, and $x_3 = 1/m$ and recast (2) as follows

$$\begin{cases} x_1 + x_2 = \hat{\mu}_2, \\ 2x_2^2 + 4x_2x_1 + (1 + x_3)x_1^2 = \hat{\mu}_4, \\ 6x_2^3 + 9x_2(1+x_3)x_1^2 + x_1^3(1+x_3)(1+2x_3) + 18x_1x_2^2 = \hat{\mu}_6. \end{cases} \tag{3}$$

Using the first and the second equations leads to the following two results

$$x_1^2(1 + x_3) = \hat{\mu}_4 - 2x_2^2 - 4x_1x_2, \;\; x_3 = \frac{b + x_1^2}{x_1^2}, \tag{4}$$

where $b = \hat{\mu}_4 - 2\hat{\mu}_2^2$. Let us proceed rewriting the third equation of (3) as

$$6x_2^3 + 9x_2\left[x_1^2(1 + x_3)\right] + \left[x_1^2(1 + x_3)\right]x_1(1 + 2x_3) \\ + 18x_1x_2^2 - \hat{\mu}_6 = 0. \tag{5}$$

Using the first equation of (4), the left-hand-side of (5) can be recast as

$$- 12x_2^3 + 9\hat{\mu}_4x_2 - 18x_1x_2^2 \\ - \hat{\mu}_6 + (\hat{\mu}_4 - 2x_2^2 - 4x_1x_2)x_1(1 + 2x_3). \tag{6}$$

Exploiting (4), the term $x_1(1+2x_3)$ can be written as $x_1(1+2x_3) = \frac{2b+3x_1^2}{x_1}$. Thus, (5) becomes

$$x_1x_2(-12x_2^2 - 12x_1^2 + c - 24x_1x_2) + 3\hat{\mu}_4x_1^2 \\ - \hat{\mu}_6x_1 - 4bx_2^2 + d = 0, \tag{7}$$

where $c = 9\hat{\mu}_4 - 8b$, and $d = 2\hat{\mu}_4b$. Now, replace x_2 with $\hat{\mu}_2 - x_1$ to recast the last equation as

$$x_1(\hat{\mu}_2 - x_1)\left[-12(\hat{\mu}_2 - x_1)^2 - 12x_1^2 + c - 24x_1(\hat{\mu}_2 - x_1)\right] \\ + 3\hat{\mu}_4x_1^2 - \hat{\mu}_6x_1^2 - \hat{\mu}_6x_1 - 4b(\hat{\mu}_2 - x_1)^2 + d = 0 \\ \Rightarrow x_1^2(3\hat{\mu}_4 - e - 4b) + x_1(e\hat{\mu}_2 - \hat{\mu}_6 + 8\hat{\mu}_2b) \\ + d - 4\hat{\mu}_2^2b = 0, \tag{8}$$

where $e = c - 12\hat{\mu}_2^2$. Therefore, we have obtained a second-order equation which yields two possible values for x_1. It is clear that the admissible solutions must belong to $\mathbb{R}^+$ and they exist if a (sufficiently) large data size has been used by the (consistent) estimators of the statistical moments $\hat{\mu}_2$, $\hat{\mu}_4$, and $\hat{\mu}_6$. It follows that, given a solution $\hat{x}_1$, then using the first equation of (3) and the second of (4) it is possible to find

[4]If the estimators are consistent, then for sufficiently large values of K, the system admits solution with probability 1.

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estimates of x_2 and x_3, respectively. It is important to observe that if $(\hat{x}_1, \hat{x}_2, \hat{x}_3)$ is a solution of the system, then it represents the sought estimate if $(\hat{x}_1, \hat{x}_2, \hat{x}_3) \in \{\mathbb{R}^+ \times \mathbb{R}^+ \times \mathbb{R}^+\}$. When more than one admissible solution exists, we select the solution which returns the maximum value of the joint likelihood function of the set R given by $\mathcal{L}(\sigma^2, m, \Omega) = \prod_{l=1}^{L} \mathcal{L}_{r_l}(\sigma^2, m, \Omega)$, where $\mathcal{L}_{r_l}(\sigma^2, m, \Omega)$ is derived in the appendix.

Summarizing, the proposed estimator of the Rician K-factor in the presence of Nakagami-m shadowing is $\hat{K} = \hat{x}_1/\hat{x}_2$. This estimator is referred to in the following as Nakagami-based K-estimator (NB-E). As last remark, note that the NB-E requires an additional computational burden with respect to the conventional approach due to the computation of a consistent estimator of the noncentral moment of order 6 and possibly the joint likelihood function, which requires numerical integration routines.

III. Numerical Examples and Discussion

In this section, we investigate the estimation performance of the proposed procedure as a function of the actual value of K and the shape parameter of the Nakagami-m shadowing. For comparison purposes, we also consider the conventional estimator (C-E) of the Rician K-factor, whose expression is [4] $\hat{K}_{conv} = \sqrt{2\hat{\mu}_2^2 - \hat{\mu}_4}/(\hat{\mu}_2 - \sqrt{2\hat{\mu}_2^2 - \hat{\mu}_4})$. It is important to stress here that both estimators are fed by data from a single receiver (unlike in [7]).

Since a closed-form expression for the pdf of the proposed estimator is not available, the numerical examples are obtained by means of standard Monte Carlo counting techniques over 1000 independent trials and 10^5 independent samples. Moreover, all figures assume the Nakagami-m shadowing and unit power for the diffuse component, namely $\sigma^2 = 1$.

In Figure 1 and 2, we plot the (mean) estimated value of K (together with its standard deviation as a confidence interval) versus the actual value of K for two different values of m. More precisely, Figure 1 assumes a small value for m, whereas in Figure 2 m is large. The figures highlight that the NB-E has a negligible bias for both values of m, unlike the conventional estimator, whose bias decreases as m increases. Figures 3 and 4 confirm the observed trend for the bias of the C-E. As a matter of fact, given K, it strongly depends on the multipath parameter m.

As a final remark, we observe that, in practice, the conventional estimator requires much less data sizes to obtain stable outcomes, but exhibits a significant bias that may result in a systematic erroneous evaluation of the Rician K-factor. As shown in Figures 1 and 2, this effect increases for large values of K, which correspond to higher LoS power levels, and for small values of the shape parameter m, namely when the level of shadowing increases [11], as depicted in Figures 3 and 4. This results in a large estimation error that cannot be corrected even for large data sizes. Conversely, the proposed estimator is able to achieve consistent estimates (the NB-E overlaps the actual values of K in the Figures 1-4) for all the assumed values for K and m.

IV. Conclusions

A novel estimator of the Rician K-factor has been conceived and assessed in this letter. It is based on the Rician shadowed model where the amplitude of the LoS component is modeled in terms of a Nakagami-m random variable. This model leads to a tractable mathematical framework and exhibits a good match to experimental data in the context of LMS communications. The proposed procedure exploits both the likelihood function of the received samples, whose expression has been derived, and the method of moments to estimate the numerator and denominator of the Rician factor. The performance analysis has shown that the new estimator is able to avoid the systematic bias of the conventional estimator at least for the considered parameters. Finally, in the context of parameter estimation, the design of suboptimum procedures for likelihood maximization would be of interest and is part of the current research activity.

Appendix

In this appendix, the expression of the likelihood function for the lth sample is derived. Specifically, by the *Law of Total Probability*, it is possible to write

$$h_{r_l}(r_l; \sigma^2, m, \Omega) = \int_0^{2\pi} \int_0^{+\infty} h_{r_l|s_l\varphi_l}(r_l; s_l, \varphi_l, \sigma^2) \frac{g(s_l; m, \Omega)}{2\pi} ds_l d\varphi_l \quad (9)$$

where $h_{r_l}(\cdot; \cdot, \cdot, \cdot)$ is the probability density function (pdf) of r_l, $g(s_l; m, \Omega)$ is the pdf of s_l, and $h_{r_l|s_l\varphi_l}(\cdot; \cdot, \cdot, \cdot)$ is the conditional pdf of r_l given s_l and φ_l. Now, observe that, given s_l and φ_l, $r_l \sim \mathcal{CN}_1(s_l e^{j\varphi_l}, \sigma^2)$, then (9) can be recast as

$$h_{r_l}(r_l; \sigma^2, m, \Omega) = C_l \int_0^{2\pi} \int_0^{+\infty} s_l^{\mu-1} \exp\{-\beta s_l^2 - \gamma s_l\} ds_l d\varphi_l, \quad (10)$$

where $C_l = [m^m \exp\{-|r_l|^2/\sigma^2\}]/[(\pi\sigma)^2\Gamma(m)\Omega^m]$, $\beta = 1/\sigma^2 + m/\Omega > 0$, $\gamma(\varphi_l) = -2\Re\{r_l e^{-j\varphi_l}\}/\sigma^2$, and $\mu = 2m > 0$. The integral with respect to s_l can be solved resorting to [5, Section 3.462] to obtain

$$(10) = A \int_0^{2\pi} \exp\left(\frac{(\gamma(\varphi_l))^2}{8\beta}\right) D_{-\mu}\left(\frac{\gamma(\varphi_l)}{\sqrt{2\beta}}\right) d\varphi_l,$$

where $A = C_l(2\beta)^{-\mu/2}\Gamma(\mu)$, and

$$D_\mu(z) = 2^{\mu/2} e^{-z^2/4} \left[\sqrt{\pi}/\Gamma\left[(1-\mu)/2\right] \Phi\left(-\mu/2, 1/2; z^2/2\right) - \sqrt{2\pi} z/\Gamma(-\mu/2) \Phi\left((1-\mu)/2, 3/2; z^2/2\right)\right]$$

is the *Parabolic Cylinder Function* [5]. Summarizing, the expression of the likelihood of r_l is[5]

$$\mathcal{L}_{r_l}(\sigma^2, m, \Omega) = h_{r_l}(r_l; \sigma^2, m, \Omega) = \frac{m^m \exp\{-|r_l|^2/\sigma^2\}}{(\pi\sigma)^2\Gamma(m)\Omega^m} \left(\frac{2}{\sigma^2} + \frac{2m}{\Omega}\right)^{-m} \Gamma(2m) \times \int_0^{2\pi} \exp\left\{\frac{\Re^2\{r_l e^{-j\varphi_l}\}}{2\sigma^4\left(\frac{1}{\sigma^4} + \frac{m}{\Omega}\right)}\right\} D_{-2m}\left(-\frac{2\Re\{r_l e^{-j\varphi_l}\}}{\sigma^2\sqrt{\frac{2}{\sigma^2} + \frac{2m}{\Omega}}}\right) d\varphi_l. \quad (11)$$

[5]Note that (11) can be evaluated by means of numerical routines.

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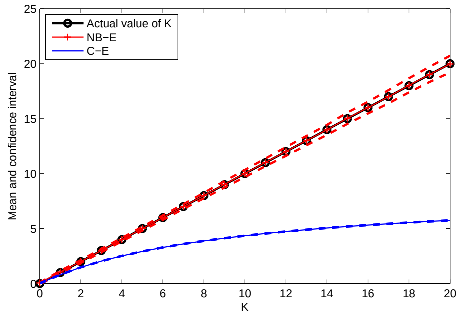

Fig. 1. The mean value (with confidence interval) of NB-E and C-E versus K-factor; $\sigma^2 = 1$, $m = 5$, and dashed lines represent the confidence interval.

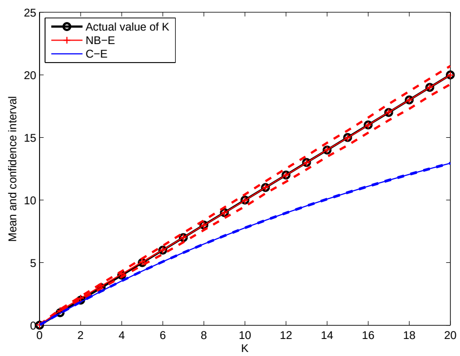

Fig. 2. The mean value (with confidence interval) of NB-E and C-E versus K-factor; $\sigma^2 = 1$, $m = 20$, and dashed lines represent the confidence interval.

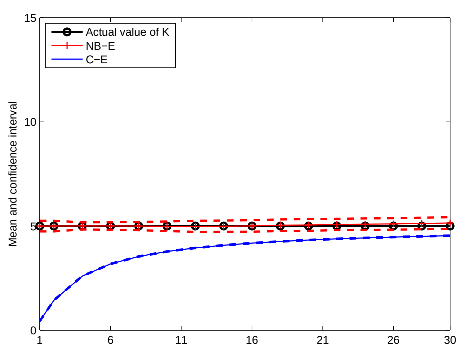

Fig. 3. The mean value (with confidence interval) of for NB-E and C-E versus m; $\sigma^2 = 1$, $K = 5$, and dashed lines represent the confidence interval.

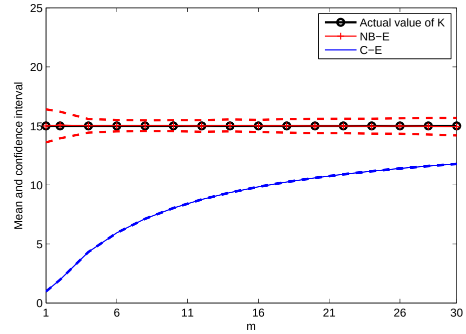

Fig. 4. The mean value (with confidence interval) of for NB-E and C-E versus m; $\sigma^2 = 1$, $K = 15$, and dashed lines represent the confidence interval.

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