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Joint mean angle of arrival, angular and Doppler spreads estimation in macrocell environments

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Abstract

In this paper, we propose a new low-complexity joint estimator of the mean angle of arrival (AoA), the angular spread (AS), and the maximum Doppler spread (DS) for single-input multiple-output (SIMO) wireless channel configurations in a macrocell environment. The non-line-of-sight (NLOS) case is considered. The space-time correlation matrix is used to jointly estimate the three parameters. Closed-form expressions are developed for the desired parameters using the modules and the phases of the cross-correlation coefficients. Simulation results show that our approach offers a better tradeoff between computational complexity and accuracy than the most recent estimators in the literature.

Keywords: Joint estimation; Mean angle of arrival; Angular spread; Maximum Doppler spread; Space-time correlation; Rayleigh channel

1 Introduction

In wireless systems, the propagation environment has a great impact on smart antenna performance. Indeed, the multipath phenomenon produces the fading of signal strength due to constructive and destructive interferences. It also induces multiple angles of arrival (AoA) and angular spreads (AS), which reduces signal quality and hence degrades the performance of smart antennas. The estimation of those parameters is crucial and would improve the potential of smart antennas.

The mean AoA and the AS are critical parameters. Their estimates are used in several applications like source localization and detection [1]. The maximum Doppler spread (DS) is also a key parameter. Indeed, it provides information about the fading severity, and its knowledge at the base station can be used for hand-off purposes [2]. It is also needed in dynamic channel assignment [2], so that it can improve link quality. In this paper, we propose a new joint estimator for the mean AoA, the AS, and the maximum DS with a low-complexity approach. This work is motivated by the need to develop a new simple and accurate approach to jointly estimate the

desired parameters since they are all required by several applications in mobile communication systems. To the best of our knowledge, there is no estimator which jointly estimates the three parameters. One can argue that two estimators among the literature could be easily combined. But implementing a different method for each parameter increases the overall computational complexity. Besides, there is room for performance improvement by recurring to a joint estimation approach while keeping overall complexity at a modest order, thereby resulting in a significantly improved performance vs. complexity trade-off. It is from this perspective that we propose in this work a low-complexity algorithm to jointly estimate the desired parameters with high accuracy.

Mean AoA and AS estimation has been studied in recent works. The maximum likelihood (ML) method is used in [3,4]. The Gaussian-Newton algorithm used in [4] shows high computational complexity, whereas in [3], a new derivative of the ML method is developed. The latter considers the problem of localizing a source by means of a sensor array for a noisy received signal. This estimator is based on two solutions, considering both high and low signal-to-noise ratio (SNR) cases. In [5], the Gaussian-Newton algorithm is applied using the estimated covariance matrix of a single-input multiple-output (SIMO) configuration. This approach provides accurate

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estimates over a high computational complexity. In [6], a simple and accurate mean AoA estimator in the case of imperfect spatial coherence is proposed. In [1] and [7], low-complexity estimators are developed. The idea of replicating the transmitting source into two virtual sources is used. Then, the mean AoA and the AS are estimated by, respectively, averaging and differentiating the two virtual AoAs. In [7], the spread root-MUSIC algorithm is used, while in [1], the two-stage (TS) approach is developed using closed-form expressions.

Several methods were developed in the context of mobile communications to estimate the maximum DS. The auto-correlation function (ACF) was exploited in [3] and [8] to offer accurate estimates. In [3], a ML method based on a polynomial approximation of the ACF is used. While the estimator developed in [8] uses the ACF derivatives and takes into account the incoming wave distribution. Unlike the method described in [3], it presents a low computational complexity. In [9], a level crossing rate (LCR) approach is proposed. It considers a novel Doppler adaptive noise suppression process in the frequency domain to reduce the effect of the additive noise. In [10-12], Azemi et al. investigate the maximum DS estimation using three different techniques. The first approach is based on the reduced interference time-frequency distribution of the received signals [10]. The second one considers the ambiguity function [11], while the proposed algorithm in [12] uses the instantaneous frequency of the received signal. The two-ray (TR) approximation proposed in [13] offers a robust maximum DS estimation. It offers a closed-form expression and considers the presence of residual carrier frequency offset (CFO), which is closer to real-life scenarios.

In this work, we consider as benchmarks the TS approach [1] and the SRM algorithm [7] for the mean AoA and AS estimation, and the TR approach [13] and the ACF-based algorithm [8] for the maximum DS estimation. These recent works were chosen because they currently offer best trade-off between estimation accuracy and computational complexity.

This paper is organized as follows: In Section 2, we describe the considered signal model then define the space-time correlation matrix. We consider here the Gaussian and the Laplacian angular distributions for the incoming AoAs [14], the most popular ones in the literature. Nonetheless, the algorithm can be applied for other distributions like the uniform one. Next, we propose our joint estimator for the mean AoA, the AS, and the maximum DS. In Section 3, we evaluate the performance of the proposed approach before drawing out our conclusions in Section 4.

Notation: We use $(\cdot)^*$ for conjugate operator, $|\cdot|$ for absolute value, $E[\cdot]$ for mathematical expectation, and \angle for phase. $\Re(\cdot)$ represents the real parts of a complex number.

We also use $(\cdot)^H$ for trans-conjugate operator. The bold uppercase and lowercase letters represent, respectively, the matrices and vectors, while the non-bold lowercase letters represent scalars.

2 Derivation of the new joint estimator

In this section, we present the new joint estimator for the desired parameters. To this end, we consider the uplink transmission over a SIMO Rayleigh channel from a single source to N_a uniform linear array (ULA) at the receiver. The received signal in baseband at the i th antenna element is modeled as follows [15]:

$$x_i(t) = \sigma_{s_i} \lim_{P \rightarrow +\infty} \frac{1}{\sqrt{P}} \sum_{p=1}^P a_p \exp j[\omega_D \cos(\theta_p)t + \phi_p] + n_i(t), \quad (1)$$

where $\sigma_{s_i}^2$ is the power of the received signal, P is the number of multipaths, a_p are random unknown complex constants normalized as follows:

$$\lim_{P \rightarrow +\infty} P^{-1} \sum_{p=1}^P |a_p|^2 = 1, \quad (2)$$

so that $\sigma_{s_i}^2 = E[|x_i(t)|^2] - \sigma_{n_i}^2$ where $\sigma_{n_i}^2$ is the power of the additive white Gaussian noise (AWGN), $n_i(t)$, at the i th antenna. The AoAs θ_p of the received signals follow an angular distribution with a mean and a standard deviation defined by the mean AoA, θ_m , and the AS, σ_θ , respectively. The phases ϕ_p are uniformly distributed over $(-\pi, \pi]$. ω_D denotes the normalized maximum DS and is given by $\omega_D = 2\pi F_D T_s$ where F_D is the Doppler frequency [15] and T_s is the sampling interval.

As mentioned before, the estimation of the mean AoA, AS, and DS is useful in several applications by improving therein the potential performance gains from smart antennas. Most mean AoA and AS estimators as in [1,6,7] consider the following spatial correlation function:

$$\begin{aligned} \mathbf{R}_{kl} &= \frac{E[x_k(t)x_l^*(t)]}{\sqrt{E[|x_k(t)|^2]E[|x_l(t)|^2]}} \\ &= \int_{-\infty}^{+\infty} P(\theta_p|\theta_m, \sigma_\theta) \exp\left(-j\frac{2\pi}{\lambda}d_{kl}\sin(\theta_m)\right) d\theta_p, \end{aligned} \quad (3)$$

where $P(\theta_p|\theta_m, \sigma_\theta)$ is the probability density function (PDF) of the incoming AoAs.

For the DS estimators, the temporal correlation function is exploited as in [3,8,13] and is defined by

$$\begin{aligned} \mathbf{R}(\tau) &= \frac{E[x_k(t)x_k^*(t+\tau)]}{E[|x_k(t)|^2]} \\ &= \int_{-\infty}^{+\infty} P(\theta_D|\theta_m, \sigma_\theta) \exp(-j\omega_D \cos(\theta_D)\tau) d\theta_D, \end{aligned} \quad (4)$$

where $P(\theta_D|\theta_m, \sigma_\theta)$ is the PDF of the Doppler angles θ_D . The latter is given by $(\theta_p - \alpha)$, where α is the direction of travel (DoT) defined as the angle between the direction of the mobile and the antenna axis as shown in Figure 1. In this work, instead of combining two methods from the ones developed in the literature, we propose a unique algorithm to jointly estimate the three parameters. To this end, we jointly exploit both the spatial and the temporal correlations. The cross-correlation matrix of the received signals is then given by

$$\mathbf{R}_{kl}(\tau) = \frac{E[x_k(t)x_l^*(t+\tau)]}{\sqrt{E[|x_k(t)|^2]E[|x_l(t)|^2]}}.$$

After some algebraic manipulation and using (2), we obtain the following expression for the cross-correlation function:

$$\mathbf{R}_{kl}(\tau) = \int_{-\pi}^{\pi} P(\theta_p; \theta_m, \sigma_\theta) \exp\left(-j\frac{2\pi}{\lambda}d_{kl}\sin(\theta_p)\right) \exp(-j\omega_D\tau\sin(\theta_p - \alpha))d\theta_p, \quad (5)$$

with d_{kl} is the distance between the k th and the l th antenna elements.

The estimated cross-correlation coefficients are given by

$$\hat{\mathbf{R}}_{kl}(\tau) = \frac{1}{N_s - \tau} \sum_{m=1}^{N_s - \tau} x_k(m)x_l^*(m + \tau), \quad (7)$$

where N_s is the number of the received signal samples.

In this paper, we consider both Gaussian and Laplacian angular distributions for the incoming AoAs [14]. Other angular distribution for the incoming AoAs can be applied like the uniform one, but this would yield to different closed-form expressions. The von Mises distribution approximate all these angular distributions over κ

parameter value, but in our approach, it does not yield to closed-form expressions of the auto-correlation and cross-correlations functions.

2.1 Gaussian angular distribution

The PDF of the Gaussian angular distribution is given by

$$P(\theta_p, \theta_m, \sigma_\theta) = \frac{1}{\sigma_\theta \sqrt{2\pi}} \exp\left[-\frac{(\theta_p - \theta_m)^2}{2\sigma_\theta^2}\right]. \quad (8)$$

The following entity is considered to solve the integral expression [16]:

$$\int_0^{+\infty} \exp(-ax^2) \cos bx \, dx = \frac{1}{2} \sqrt{\frac{\pi}{a}} \exp\left[-\frac{b^2}{4a}\right]. \quad (9)$$

In this work, we assume small ASSs, σ_θ . Indeed, in macro-cell environments, the AS does not exceed 10° [15,17,18]. In this case, the following linearization is applied to ensure regular integrals:

$$\sin(\theta_p) = \sin(\theta_m) + (\theta_p - \theta_m) \cos(\theta_m). \quad (10)$$

We obtain the following closed-form expression, $\mathbf{R}_{kl}(\tau)$, for the Gaussian angular distribution:

$$|\mathbf{R}_{kl}(\tau)| = \exp\left[-\frac{\sigma_\theta^2}{2} \left(-\omega_D\tau \cos(\theta_m - \alpha) - \frac{2\pi}{\lambda}d_{kl} \cos(\theta_m)\right)^2\right], \quad (11)$$

$$\angle \mathbf{R}_{kl}(\tau) = -\frac{2\pi}{\lambda}d_{kl} \sin(\theta_m) - \omega_D\tau \sin(\theta_m - \alpha). \quad (12)$$

In our algorithm, we consider the modules and the phases of the estimated cross-correlation coefficients. The mean AoA is estimated using, respectively, the phase of the auto-correlation, $\hat{\mathbf{R}}_{kk}(\tau)$, of the received signal at the k th antenna and the cross-correlation, $\hat{\mathbf{R}}_{kl}(\tau)$, associated to the antenna pair (k, l) as follows:

$$\hat{\theta}_m(k, l) = \arcsin\left(\frac{\angle \hat{\mathbf{R}}_{kk}(\tau) - \angle \hat{\mathbf{R}}_{kl}(\tau)}{\frac{2\pi}{\lambda}d_{kl}}\right), \quad (13)$$

$\forall k < l$ and $(k, l) \in \{1 \dots N_a\}$ with $k \neq l$.

The AS estimate is determined by exploiting the modules of the cross-correlations $\hat{\mathbf{R}}_{kj}(\tau)$, $\hat{\mathbf{R}}_{kl}(\tau)$, and the mean AoA estimates:

$$\hat{\sigma}_\theta(k, l, j) = \frac{\sqrt{-\ln(|\hat{\mathbf{R}}_{kj}(\tau)|)} - \sqrt{-\ln(|\hat{\mathbf{R}}_{kl}(\tau)|)}}{\frac{\sqrt{2\pi}}{\lambda} \cos(\hat{\theta}_m)(d_{kj} - d_{kl})}, \quad (14)$$

$\forall k < l < j$ and $(k, l, j) \in \{1 \dots N_a\}$ with $k \neq l \neq j$.

Finally, the maximum DS is deduced using both the module and phase of the cross-correlation, $\hat{\mathbf{R}}_{kl}(\tau)$, the estimated values of the mean AoA and the AS and considering the trigonometric property $(\cos(\theta_m)^2 + \sin(\theta_m)^2 = 1)$. The maximum DS estimate is then expressed as follows:

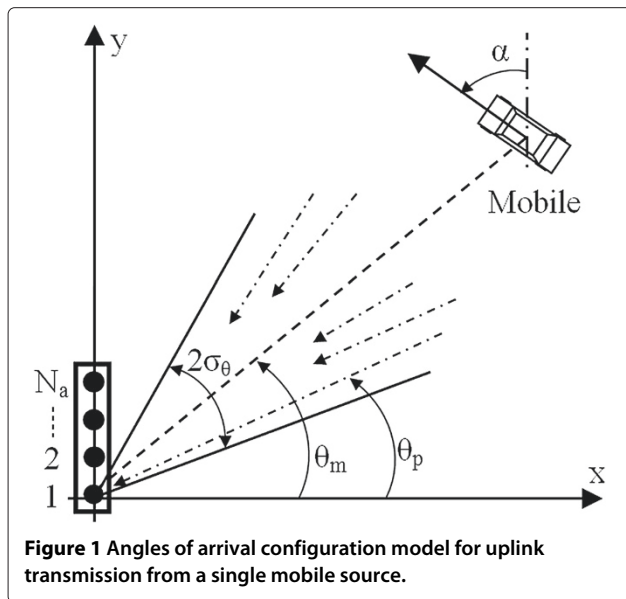


Figure 1 Angles of arrival configuration model for uplink transmission from a single mobile source.

$$\hat{\omega}(k, l) = 1/\tau \left(\sqrt{\left(\angle \hat{\mathbf{R}}_{kl}(\tau) + \frac{2\pi}{\lambda} d_{kl} \sin(\hat{\theta}_m) \right)^2 + \left(\frac{\sqrt{-\ln |\hat{\mathbf{R}}_{kl}(\tau)|}}{\hat{\sigma}_\theta} - \frac{2\pi}{\lambda} d_{kl} \cos(\hat{\theta}_m) \right)^2} \right), \quad (15)$$

$\forall k < l$ and $(k, l) \in \{1 \dots N_a\}$ with $k \neq l$.

2.2 Laplacian angular distribution

The PDF of the Laplacian angular distribution is defined by

$$P(\theta_p, \sigma_\theta, \theta_m) = \frac{1}{\sigma_\theta \sqrt{2}} \exp \left[-\frac{|\theta_p - \theta_m|}{\frac{\sigma_\theta}{\sqrt{2}}} \right] \quad (16)$$

To overcome the integral expressions in (5), we can use the following identity [16]:

$$\int_0^{+\infty} \exp(-ax) \cos bx \, dx = \frac{a}{a^2 + b^2}. \quad (17)$$

Assuming a small AS, the following approximation can be considered:

$$\cos(\theta_p) = \cos(\theta_m) - (\theta_p - \theta_m) \sin(\theta_m). \quad (18)$$

After some algebraic manipulations, we obtain the cross-correlation coefficient for the Laplacian distribution $\mathbf{R}_{kl}(\tau)$. As for the Gaussian version, we consider separately the magnitude and the phase of the cross-correlation coefficients as follows:

$$|\mathbf{R}_{kl}(\tau)| = \frac{1}{1 + \frac{\sigma_\theta^2}{2} \left[\omega_D \tau \cos(\theta_m - \alpha) + \frac{2\pi}{\lambda} d_{kl} \cos(\theta_m) \right]^2}, \quad (19)$$

$$\angle \mathbf{R}_{kl}(\tau) = -\frac{2\pi}{\lambda} d_{kl} \sin(\theta_m) - \omega_D \tau \sin(\theta_m - \alpha). \quad (20)$$

The mean AoA is then obtained as for the Gaussian case (13). Using all the cross-correlation coefficients defined in (19) for two antenna couples (k, l) and (k, j) , we obtain the following AS estimate:

$$\hat{\sigma}_\theta(k, l, j) = \frac{\sqrt{\frac{2}{|\hat{\mathbf{R}}_{kl}(\tau)|} - 2} - \sqrt{\frac{2}{|\hat{\mathbf{R}}_{kj}(\tau)|} - 2}}{\frac{2\pi}{\lambda} \cos(\hat{\theta}_m(k, l))(d_{kl} - d_{kj})}, \quad (21)$$

where $k, l, j \in \{1 \dots N_a\}$ and $k \neq l \neq j$.

The maximum DS estimate is then deduced using the addition of the square $|\hat{\mathbf{R}}_{kl}(\tau)|$ in (19) and $\angle \hat{\mathbf{R}}_{kl}(\tau)$ in (20):

where $k, l \in \{1 \dots N_a\}$ and $k \neq l$.

The final estimates are then obtained by averaging over antenna branches separated by a half wavelength. As one can notice, only the cross-correlation matrix is used to jointly estimate the three parameters. Contrarily to the methods developed in [1,13], the proposed algorithm does not require the additive noise power estimation nor the eigenvalue decomposition of the correlation matrix, which reduces considerably the overall computational complexity. In the next section, we study both performance and complexity of our joint estimator.

3 Simulation results

We illustrate the performance of the new joint estimator (JE) in macrocell environments by means of $N_b = 1,000$ Monte-Carlo simulations. We consider $N_s = 1,024$ samples and a ULA with $N_a = 5$ elements spaced by a half wavelength. We also use the non-selective frequency Rayleigh channel model described in [19]. The simulations are CFO free and run at SNR = 20 dB and the sampling interval is set to $T_s = \frac{1}{1,500}$ s. Two time lags τ are needed to ensure high accuracy. This is why we consider in this section $\tau = 1$ for the mean AoA and the AS estimation and $\tau = 100$ for the maximum DS estimation. However, if the targeted application does not require accurate estimates, one time lag could be used then. The sampling rate $1/T_s$ is sufficiently small to guarantee $\tau T_s \ll 1$. Exhaustive simulations were performed and showed that averaging over all antenna pairs induces several possible AoAs that give the same phase difference. This is why only the closest antenna elements ($d = \lambda/2$) are considered for the three-parameter estimation to avoid the ambiguity problem. In that case, only the first subdiagonal of the cross-correlation matrix is used. The subdiagonal cross-correlation coefficients are nominally equal; this is why considering more antenna elements would not improve the estimation accuracy of the joint estimation.

To evaluate our JE, we perform a comparative study in terms of normalized root mean square error (NRMSE) given by

$$\hat{\omega}_D(k, l) = 1/\tau \left(\sqrt{\left(\angle \hat{\mathbf{R}}_{kl}(\tau) + 2\pi d_{kl} \sin(\hat{\theta}_m(k, l)) \right)^2 + \left(\frac{\sqrt{\frac{2}{|\hat{\mathbf{R}}_{kl}(\tau)|} - 2}}{\hat{\sigma}_\theta(k, l, j)} - 2\pi d_{kl} \cos(\hat{\theta}_m(k, l)) \right)^2} \right), \quad (22)$$

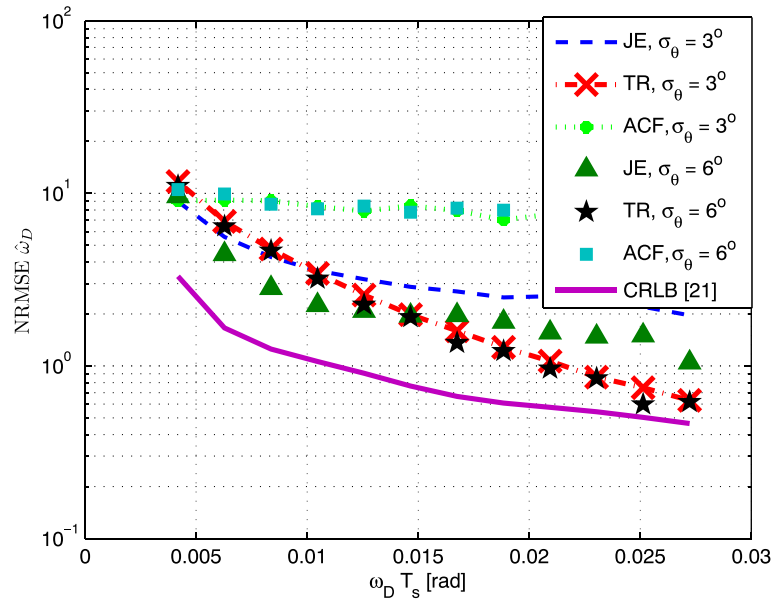


Figure 2 NRMSE of the mean AoA estimates at $\sigma_\theta = 6^\circ$ for the Gaussian angular distribution.

$$\text{NRMSE}(\hat{\eta}) = \frac{\sqrt{E\{(\eta - \hat{\eta})^2\}}}{\eta}. \quad (23)$$

We evaluate our approach by comparing it to the TS approach [1] and the SRM [7] for the mean AoA and the AS estimation. For the maximum DS, we take as benchmark the TR approach [13] and the ACF-based algorithm [8]. We also compare these estimators to the Cramér-Rao lower bounds (CRLBs). For the mean AoA and AS, we

consider the CRLB developed in [20]. For the maximum DS, we use the one developed in [21]. The used CRLBs for each given parameter assume the two others to be perfectly known and hence very likely overestimate the true joint CRLB.

Figures 2 and 3 show the NRMSE of the mean AoA estimates using the JE, TS, and SRM approaches at $\sigma_\theta = 6^\circ$ for both Doppler frequencies $F_D = 50$ and 100 Hz, respectively, for the Gaussian and the Laplacian angular

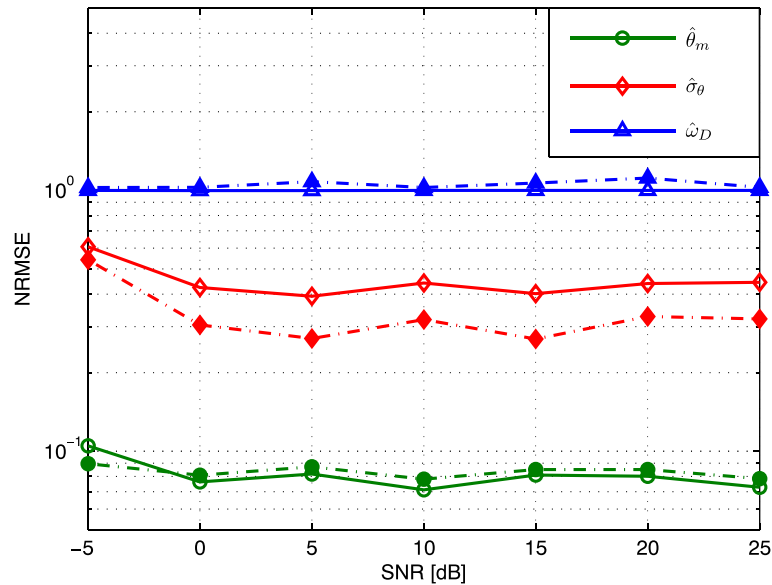


Figure 3 NRMSE of the mean AoA estimates at $\sigma_\theta = 6^\circ$ for the Laplacian angular distribution.

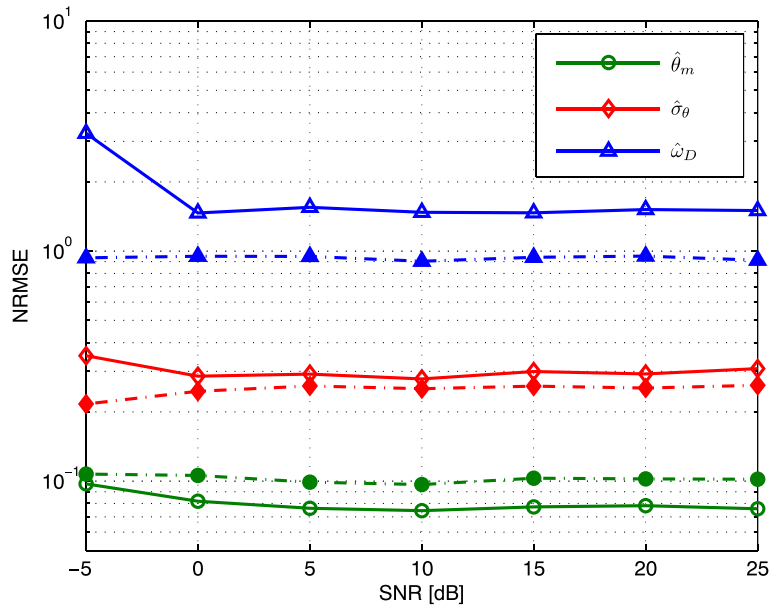


Figure 4 NRMSE of the AS estimates at $\theta_m = 10^\circ$ for the Gaussian angular distribution.

distributions. We notice that for both high and low F_D values, the SRM algorithm offers a lower error rate than the TS approach. The TS approach offers the same error rate than the JE estimator for high mean AoA values, while for low values, the JE provides a higher accuracy. For low θ_m values, the JE and the SRM estimators have almost the same performance, while for high mean AoA values, the JE outperforms the SRM algorithm.

For the AS estimation, as shown in Figures 4 and 5, the TS and JE approaches have similar error rate for low AS values. The JE estimator achieves a lower NRMSE than the TS approach [1] for high AS region where accuracy is precisely more beneficial and is the most encountered in practice. The inaccuracy shown by the TS approach for mean AoA and AS estimation is due to the approximation of the AS angular distribution while our

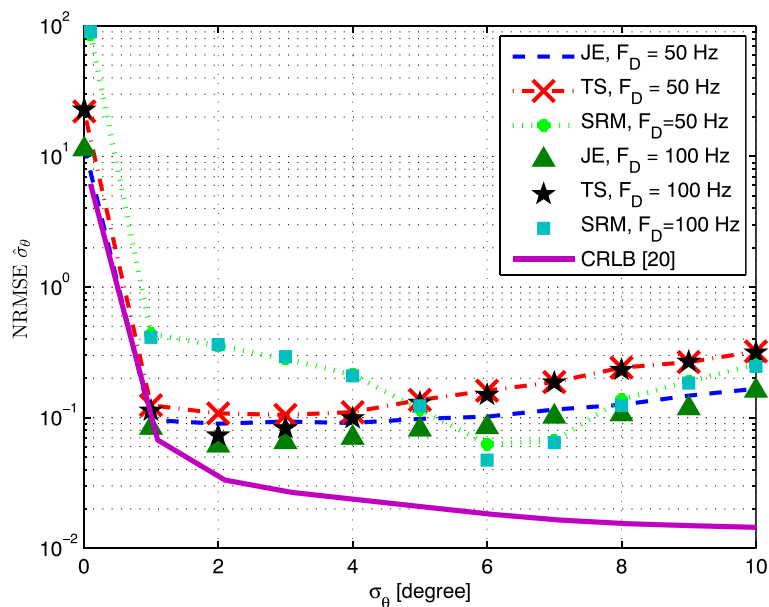


Figure 5 NRMSE of the AS estimates at $\theta_m = 10^\circ$ for the Laplacian angular distribution.

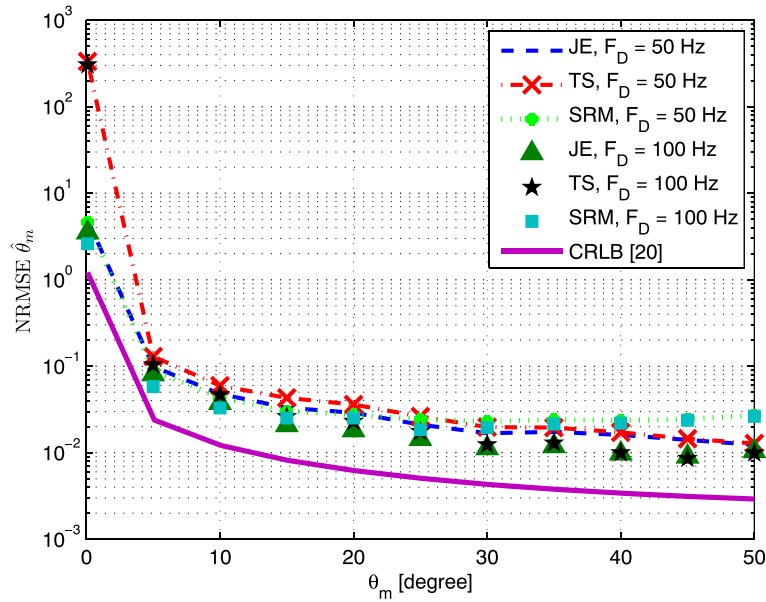


Figure 6 NRMSE of the maximum DS estimates at $\theta_m = 20^\circ$ for the Gaussian angular distribution.

algorithm considers an exact expression. Indeed, the proposed JE offers accurate estimates even for small ASs, while the SRM algorithm offers higher NRMSE's. For high AS values, the SRM and JE estimators have similar performances. We note that for both mean AoA and AS estimates, we obtain a difference less than 1 dB between the NRMSEs given by the JE estimator and the CRLB. We

note that, for low AS values, the JE NRMSEs are almost optimal, since they coincide with the CRLB.

For the maximum DS estimation, we notice in Figures 6 and 7 that the JE and TR approaches [13] perform nearly the same in terms of NRMSEs, while the ACF algorithm provides higher error rate than the TR and JE ones for both low and high ω_D values. At high ω_D values,

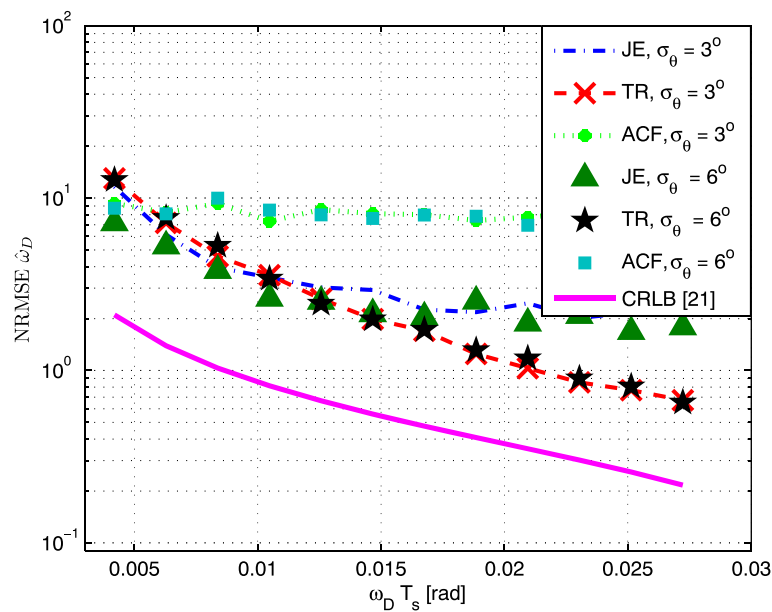


Figure 7 NRMSE of the maximum DS estimates at $\sigma_\theta = 3^\circ$ for the Laplacian angular distribution.

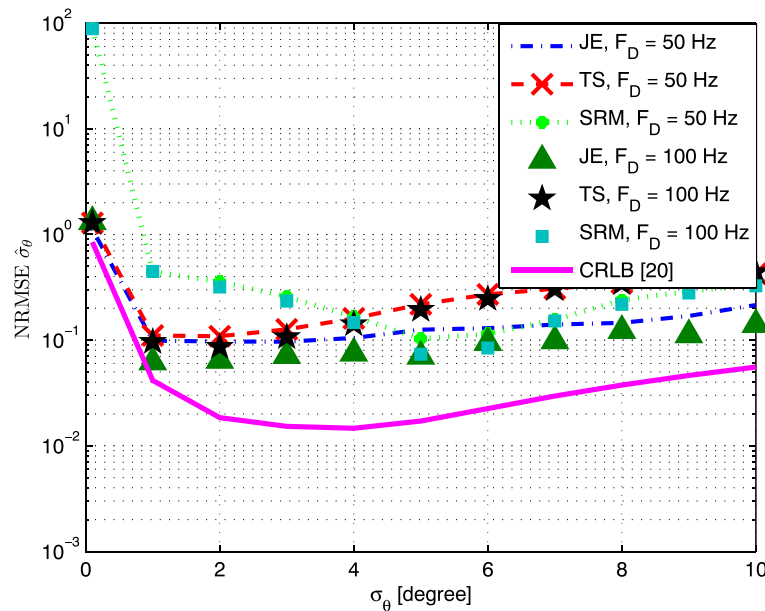


Figure 8 NRMSE of mean AoA, AS, and maximum DS vs. SNR ($F_D = 5$ Hz, $\sigma_\theta = 6^\circ$, and $\theta_m = 20^\circ$) for Gaussian angular distribution. The dashed lines for TS and TR estimators.

TR estimator outperforms the JE one. While at low ω_D , the JE yields to more accurate estimates. Since T_s is extremely small, ω_D is as well, even if operating at relatively high Doppler or mobility. Hence, accuracy is precisely more needed in the low normalized DS region, the most encountered in practice in today's high data rate transmissions characterizing 3G/4G technologies and

beyond. We notice that the TR approach considers p time lags with $p \in [0 \dots 19]$, while our new method uses only two time lags. The first is ($\tau = 1$) for the mean AoA and AS estimation. For the maximum DS estimation, we determine empirically the second time lag ($\tau = 100$). Moreover, our approach allows the joint estimation of the three parameters.

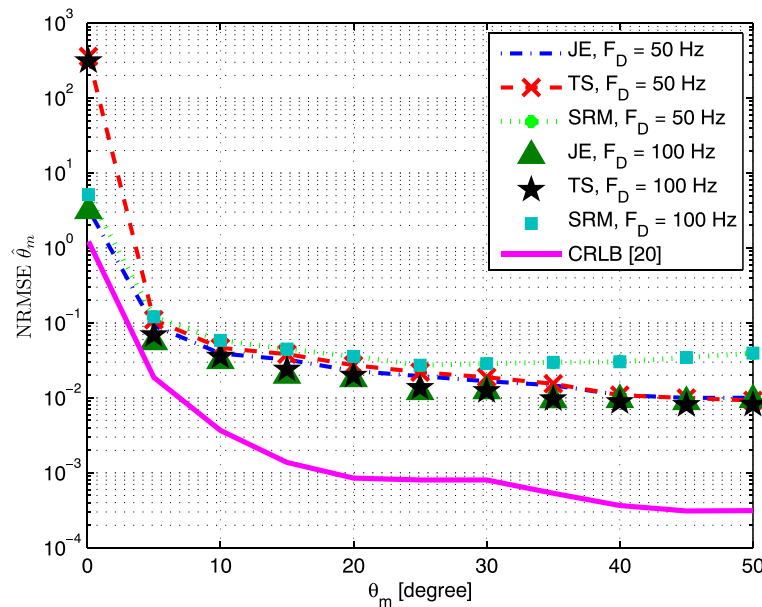


Figure 9 NRMSE of mean AoA, AS, and maximum DS vs. SNR ($F_D = 5$ Hz, $\sigma_\theta = 6^\circ$, and $\theta_m = 20^\circ$) for Laplacian angular distribution. The dashed lines for TS and TR estimators.

Table 1 Performance and complexity comparison

	JE	TS	TR	TS and TR combined
Joint estimation capability	Yes (3/3)	Partly (2/3)	No (1/3)	Yes (3/3)
AS accuracy at practical high values	+	—	N.A.	—
AoA accuracy	+	—	N.A.	—
DS accuracy at practical low values	+	N.A.	—	—
Complexity order (floating-point operations)	$N_s N_a^2 - N_a^2$	$N_s N_a^2$	$N_a (N_s - 1)(p + 1)^3$	$N_s N_a^2 + (N_s - 1)N_a (p + 1)^3$

N.A., not applicable.

In order to study the robustness of our algorithm against the additive noise effect, we illustrate in Figures 8 and 9 the estimation performance of the three parameters vs. the SNR for both the Gaussian and the Laplacian angular distributions. We take as benchmark the TS and TR algorithms in dashed lines, because these approaches use the eigenvalue decomposition of the cross-correlation matrix to estimate the additive noise power and to reduce its effect. The proposed JE does not require such procedure since the cross-correlation coefficients are nominally noise free, i.e., $E[n_k(t) n_l^*(t - \tau)] = 0$.

As one can notice, both methods seem unaffected by the SNR values variation. Figures 8 and 9 show that JE offers better estimation accuracy than the TS approach even at low SNR values for mean AoA. For AS estimation, the two approaches present close NRMSEs. For the maximum DS estimation, the TR approach outperforms our JE at the expense of a noticeably higher complexity.

In the following, we compare in complexity our algorithm with the TR, ACF, TS, and SRM approaches. Indeed, the TS and SRM approaches have a complexity order of $N_s N_a^2$ floating-point operations, while the JE presents a complexity order of $(N_s - 1)N_a^2$ floating-point operations. For the maximum DS estimation, our algorithm provides a similar estimation error as the TR and ACF approaches. Indeed, the TR uses around $p = 20$ correlation coefficients and the ACF uses $L = 15$ time lags, while our method considers only two time lags ($\tau = 1$ and $\tau = 100$). Hence, the TR complexity around $N_a(N_s - 1)(p + 1)^3$ floating-point operations [13]. The ACF complexity around $N_a(N_s - 1)(L + 1)^3$ floating-point operations. Both approaches have a higher complexity than the JE's. We could increase the temporal correlation lags used in our approach in order to improve the maximum DS estimation accuracy especially for high ω_D values, but this would increase the overall complexity as well. In fact, combining the TS algorithm and the TR approach or the SRM and ACF algorithms presents an overall estimation complexity of the three parameters around $N_s N_a^2 + N_a(N_s - 1)(L + 1)^3$ floating-point operations, whereas our approach provides accurate estimates for the three desired parameters with a single algorithm

and a lower computational complexity. The complexities of the JE and TS approaches are summarized in Table 1.

4 Conclusions

In this paper, we proposed a new low-complexity approach to jointly estimate the mean AoA, the AS, and the maximum DS in macrocell environments. The magnitudes and the phases of the cross-correlation matrix were used to estimate the three parameters. We developed the joint estimation algorithm for both the Gaussian and the Laplacian angular distributions in a NLOS scenario. Simulation results showed that our method provides more accurate estimates of the mean AoA and the AS than the TS and SRM approaches. For the maximum DS estimation, the new joint estimator outperforms the TR and ACF approaches at small DSs with lower computational complexity.

Competing interests

The authors declare that they have no competing interests.

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References

1. M Souden, S Affes, J Benesty, A two-stage approach to estimate the angles of arrival and the angular spreads of locally scattered sources. *IEEE Trans. Signal Process.* **56**(5), 1968–1983 (2008)
2. M Lee, D Cho, A new adaptive power control scheme based on mobile velocity in wireless mobile communication systems. *IEEE Vehicular Technol. Conf.* **4**, 2878–2882 (2001)
3. O Besson, F Vincent, P Stoica, A Gershman, Approximate maximum likelihood estimators for array processing in multiplicative noise environments. *IEEE Trans. Signal Process.* **48**(9), 2185–2194 (2000)
4. S Kikuchi, A Sano, H Tsuji, R Miura, A novel approach to mobile-terminal positioning using single array antenna in urban environments. *IEEE Conf. Vehicular Technol. VTC-Fall Conf.* **2**, 1010–1014 (2003)

5. T Trump, B Ottersen, Estimation of nominal direction of arrival and angular spread using an array of sensors. *Signal Process.* **50**(1–2), 57–69 (1996)
6. O Besson, P Stoica, AB Gershman, Simple and accurate direction of arrival estimator in the case of imperfect spatial coherence. *IEEE Trans. Signal Process.* **49**(4), 730–737 (2001)
7. M Bengtsson, B Ottersten, Low-complexity estimators for distributed sources. *IEEE Trans. Signal Process.* **48**(8), 2185–2194 (2000)
8. C Tepedelenlioglu, GB Giannakis, On velocity estimation and correlation properties of narrow-band mobile communication channels. *IEEE Trans. Vehicular Technol.* **50**(4), 1039–1052 (2001)
9. G Park, D Hong, C Kang, Level crossing rate estimation with Doppler adaptive noise suppression technique in frequency domain. *IEEE Conf. Vehicular Technol. VTC-Fall*, **2**, 1192–1195 (2003)
10. S Nasseh, G Azemi, Doppler spread estimation in microcellular systems using reduced interference time-frequency distribution of the received signals, in *IEEE Proceedings of Iranian Conference on Electrical Engineering* (Isfahan, 11–13 May 2010)
11. G Azemi, S Nasseh, Doppler spread estimation in mobile communication systems using the ambiguity function of the received signals, in *2009 IEEE 70th Vehicular Technology Conference Fall (VTC 2009-Fall)* (Anchorage, 20–23 Sept 2009)
12. G Azemi, B Senadji, B Boashash, Mobile unit velocity estimation in micro-cells based on the instantaneous frequency of the received signal. *IEEE Trans. Vehicular Technol.* **53**, 716–724 (2004)
13. M Souden, S Affes, J Benesty, R Bahroun, Robust Doppler spread estimation in the presence of a residual carrier frequency offset. *IEEE Trans. Signal Process.* **57**, 4148–4153 (2009)
14. 3rd Generation Partnership Project; Technical Specification Group Radio Access Network; Spatial channel model for multiple input multiple output (MIMO) simulations (3GPP TR 25.996 V11.0.0). (2012)
15. A Abdi, M Kaveh, Parametric modeling and estimation of the spatial characteristics of a source with local scattering. *IEEE Int. Conf. Acoustics Speech Signal Process.* **3**, 2821–2824 (2002)
16. A Jeffrey, Zwillinger, D (eds.), *Table of Integrals, Series, and Products* (Elsevier, New York, 2007)
17. SI-METRA ist-2000-30148, final report (2003)
18. I Bousnina, A Stéphenne, S Affes, A Samet, A new low-complexity angular spread estimator in the presence of line-of-sight with angular distribution selection. *EURASIP J. Adv. Signal Process.* **2011**(88), 1–16 (2011)
19. A Stéphenne, B Champagne, Effective multi-path vector channel simulator for antenna array systems. *IEEE Trans. Vehicular Technol.* **49**(6), 2370–2381 (2000)
20. T Trump, B Ottersten, Estimation of nominal direction of arrival and angular spread using an array of sensors. *Elsevier Signal Processing special issue on subspace methods, part I: array signal processing subspace computations.* **50**(1–2), 57–69 (1996)
21. C Tepedelenlioglu, Performance analysis of velocity (Doppler) estimators in mobile communications. *IEEE Int. Conf. Acoustics Speech Signal Process. (ICASSP)*, **3**, 2201–2204 (2002)

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