

Low-Complexity Approaches for Maximum Doppler Spread Estimation in Mobile Communication Systems

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Abstract—In this paper, three different low-complexity maximum Doppler Spread (DS) estimators are compared. A single source transmitter through a Rayleigh channel scenario is considered. The first studied method is based on velocity estimation and correlation properties of narrow-band mobile communication channels. The second low-complexity considered approach is the robust Doppler Spread estimation in the presence of residual carrier frequency offset which exploits the covariance matrix of the received signal. The third one uses reduced interference time-frequency distribution of the received signals. Simulation results shows that the second approach offers lower estimation error with a good compromise between computational complexity and estimation accuracy.

Key words— Maximum Doppler Spread, derivative correlation, Two-Rays approximation, time frequency signal processing.

I. INTRODUCTION

In mobile communication systems, multipath phenomenon induces constructive and destructive interferences, which produce the fading of signal strength. The maximum Doppler Spread (DS) provide information about the fading severity and its knowledge at the base station can be used for handoff purposes [1] [2] [3]. It is also needed in dynamic channel assignment [4], so that it can improve link quality.

Several methods were developed to estimate the maximum DS in the context of mobile communications. In [5], Level Crossing Rate (LCR) approach is proposed. The maximum DS estimator based on Two-Rays approximation is presented in [6]. This estimator presents a robust maximum DS estimation by considering the Carrier Frequency Offset (CFO). Others approaches study the Doppler frequency with the assumption of an isotropic Angles of Arrivals (AoA) [7] [8]. In [9] and [10], authors take into account the incoming waves distribution. A Maximum Likelihood (ML) estimator is used in [11], it's based on a polynomial approximation of the AutoCorrelation Function (ACF). In [9] and [12], the maximum DS estimation is based on the covariance channel. The Ambiguity Function (AF) of the received signals is used in [13] to estimate the maximum DS.

In this paper, we choose three low complexity estimators from the approaches mentioned above and we compare their performances. In this work, we privilege the low-complexity

over accurate estimates. The first chosen estimator named "on velocity estimation and correlation properties of narrow-band mobile communication channels" [9]. This work is considered as a reference in many research articles. Secondly, we choose the "Robust Doppler spread estimation in the presence of a residual carrier frequency offset" developed in [6]. It is chosen because it offers closed form expression and considers the presence of residual CFO which is closer to real-life scenarios. In fact, the principle of this method consists in replicating the transmitted source into two virtual sources. Finally, we study the estimator presented in [10] named "Doppler Spread Estimation in micro cellular system", this estimator uses the reduced Interference Time-Frequency Distribution (ITFD) of the received signals. Our purpose is to determine which estimator shows the lowest estimation error.

This paper is organized as follows. In section II, the signal model is described. In section III, we present the well known estimator in [9]. In section IV, we consider the approach developed in [6] to estimate the maximum DS. In section V, we study the time frequency signal analysis presented in [10]. In section VI, we compare and discuss the Root Mean Square Error (RMSE) results.

Notation: We use $(\cdot)^*$ for conjugate operator, $|\cdot|$ for Absolute value, $E[\cdot]$ for mathematical expectation, \angle for phase. $\Re(\cdot)$ represent 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.

II. SIGNAL MODEL

We consider the up link transmission over a SIMO (Single Input Multiple Output) configuration, with N_a Uniform Linear Array (ULA) at the receiver and a single source in a Rayleigh channel. The received signal at the i^{th} antenna element in band-pass for an uniform distribution is modeled as follow [9]:

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

where $\sigma_{x_i}^2$ is the power of the received signal, P is the number of multi paths, a_p are deterministic complex constants normalized to satisfy $\lim_{P \rightarrow +\infty} p^{-1} \sum_{p=1}^P |a_p|^2 = 1$, so that $\sigma_{x_i}^2 = E[|x(t)|^2] - \sigma_{n_i}^2$, with $\sigma_{n_i}^2$ is the power of the Additive White Gaussian Noise (AWGN) $n_i(t)$. The maximum DS is denoted by ω_D , θ_p and ϕ_p are, respectively, the independent and identically distributed (iid) Doppler angles and phases. The base station and the mobile are considered far enough from one another so as to create a near planar wavefront over the antenna-array surface. In this case, the antenna elements at reception admit the same mean AoA, Angular Spread (AS) and maximum DS.

III. ESTIMATOR BASED ON CORRELATION FUNCTION

This estimator is developed by Tepedelenlioglu and Giannakis in [9] for a Single Input Single Output (SISO) configuration. In our work, we develop it for a Single Input Multiple Output (SIMO) configuration. This estimator is based on the ACF of the received signal, $\mathbf{R}(\tau)$, for a large number of multi paths P , which ensures $x_i(t)$ to be a Gaussian process due to the central limit theorem. The correlation function is expressed as:

$$\mathbf{R}_{x_i}(\tau) = E[x_i(t) x_i^*(t + \tau)]. \quad (2)$$

Authors consider the Von-Mises as an angular probability distribution of the incoming waves:

$$p(\theta) = \frac{1}{2\pi I_0(\kappa)} \exp(\kappa \cos(\theta - \alpha)), \quad (3)$$

where $I_n(\kappa)$ is the n^{th} order modified Bessel function of the first kind, κ is the beam width and α is the mean AoA. Using the correlation function and the Von-Mises distribution, the ACF can be written as follows:

$$r(\tau) = \frac{\sigma_{x_i}^2}{K+1} \frac{J_0(\sqrt{-\beta^2 + \omega_D^2 \tau^2} - 2j\beta \cos(\alpha)\omega_D \tau)}{I_0(\beta)}, \quad (4)$$

where $\omega_d = 2\pi F_D$, $J_0(\cdot)$ is the *zero*th-order Bessel function of the first kind and K is the Ricean K -factor. In [9], to overcome the mathematical resolution difficulty the Rayleigh channel and uniform distribution are considered with ($K = \beta = 0$) and neglect the subdiagonals of the autocorrelation matrix. The ACF becomes:

$$r(\tau) = \sigma_{x_i}^2 J_0(\omega_D \tau). \quad (5)$$

The derivatives of the ACF at zero, $\mathbf{R}(0)$ are giving by:

$$\mathbf{R}(0) = \sigma_{x_i}^2 \mathbf{I}, \quad (6)$$

$$\mathbf{R}'(0) = -j\omega_D \sigma_{x_i}^2 \left(\frac{\cos(\alpha) I_1(\kappa)}{I_0(\beta)} \right) \mathbf{I}, \quad (7)$$

$$\mathbf{R}''(0) = -\omega_D^2 \frac{\sigma_{x_i}^2}{2} \left(1 + \frac{\cos(2\alpha) I_2(\beta)}{I_0(\beta)} \right) \mathbf{I}. \quad (8)$$

To determine the effect of directional scattering and Line Of Sight (LOS) component on the estimator, the LCR is used and it is given by:

$$LCR(R) = \int_0^\infty |\tilde{R}| P_{|\tilde{x}_i|, |x_i|}(\tilde{R}, R) d\tilde{R}, \quad (9)$$

where R is the level with positive slope and $P_{|\tilde{x}_i|, |x_i|}$ is the joint Probability Density Function (PDF) of the envelope. The use of (9) relates the LCR to the AoAs distribution. The signal model in (1) allows to rewrite the auto covariance of $|x_i(t)|^2$ in a closed form expression as follows:

$$C_{|x_i|^2}(\tau) = \sigma_{x_i}^2 J_0^2(\omega_D \tau). \quad (10)$$

Based on the LCR study in [9], authors propose to neglect the effect of the LOS component. So that, the $\hat{\omega}_D$ estimator is expressed as:

$$\hat{\omega}_D = \sqrt{\frac{-2 \text{Tr}[\hat{\mathbf{R}}''(0)]}{\text{Tr}[\hat{\mathbf{R}}(0)]}}. \quad (11)$$

To estimate the maximum DS, $\hat{\omega}_D$, we have first to estimate the second derivative of the ACF $\hat{\mathbf{R}}_{x_i}''(0)$. The latter is computed using L lags of the ACF, $\{\hat{r}_{x_i}(lT_s)\}_{l=1}^L$, with $LT_s \ll 1$, T_s is the sampling time. Then, we compute the estimate of the n^{th} derivative of $\hat{r}_{x_i}(0)$ by the following expression:

$$\hat{\mathbf{R}}^{(n)}(0) = \frac{n \hat{a}_n}{T_s^n}, \quad (12)$$

where \hat{a}_k are found using the least square minimization solution, as follows:

$$\hat{a}_k = \arg \left(\min_{a_k} \sum_{l=0}^L |\text{Tr}[\hat{\mathbf{R}}(lT_s)] - \sum_{k=0}^2 a_k l^k|^2 \right) \quad (13)$$

The maximum DS estimator based on correlation function steps can be summarized in this algorithm:

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| (i) Calculate the covariance matrix (2),
(ii) Estimate $\hat{\mathbf{R}}''(0)$ by averaging over L lags as $\{\text{Tr}[\hat{\mathbf{R}}(lT_s)]\}_{l=1}^L$,
(iii) Estimate the n^{th} derivative using (12) and (13),
(iv) Estimate $\hat{\omega}_D$ as in (11). |
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Table I
MAXIMUM DS ESTIMATOR BASED ON CORRELATION FUNCTION
ALGORITHM

We implement the signal model in (1) with a single source and five sensors, $N_a = 5$, at the reception. We also consider 1000 realizations.

In Fig 1, we study the effect of the Signal Noise Ratio (SNR) on $\hat{\omega}_D$ estimation at different F_D values. The estimation is insensitive to the SNR variation. We notice, a reasonable RMSE at low F_D values. However, for high F_D values, the RMSE increases significantly. In [9], the authors consider $n \in \{0, 1, 2\}$ where n is the derivative index, we propose to study the effect of n on the velocity estimation by comparing the RMSE results for two derivative indexes set as $n_1 \in \{0, 1, 2\}$ and $n_2 \in \{1, 2, 4\}$. As one can notice, the use of n_2 would deteriorates the performance of the estimator. Indeed, as shown in Fig 2, the RMSE of $\hat{\omega}_D$ estimation with n_2 is higher than n_1 ones.

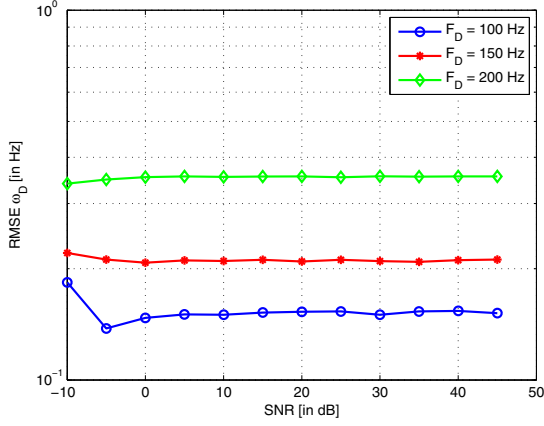


Figure 1. RMSE of $\hat{\omega}_D$ vs SNR for different values of F_d .

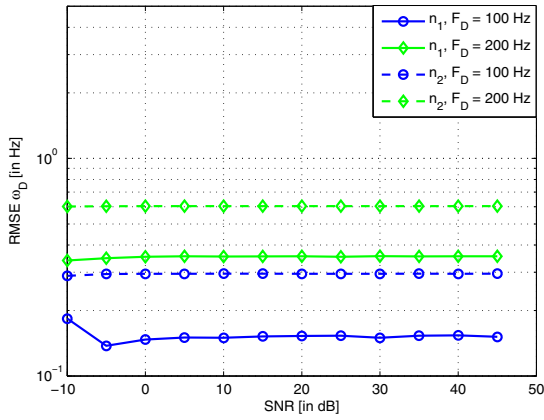


Figure 2. RMSE of $\hat{\omega}_D$ at different lags values.

One can conclude that the estimator based on correlation function gives accurate estimation with a low computational complexity. However, this method is only available for uniform distribution despite the use of the Von-Mises distribution.

IV. ESTIMATOR BASED ON TWO-RAYS APPROXIMATION

The estimator based on Two-Rays approximation is proposed recently by M. Souden and al. in [6] for a SISO configuration. In our work, we develop it for a SIMO configuration. The covariance matrix is used to estimate the maximum DS even in the presence of CFO denoted by f_c . The proposed approach is based on an approximation by two virtual, closely spaced, uncorrelated and equi-powered sources. This approach is similar to the one used for mean AoA and AS estimator presented in [14]. The covariance matrix is expressed as follow:

$$\mathbf{R}_{x_i} = E[x_i(t)x_i^*(t + \tau)] = \mathbf{R}_h + \mathbf{R}_n, \quad (14)$$

where T_s is the sampling rate and $x_i(n T_s) = [x_i[n T_s] \dots x_i[(n + N - 1)T_s]]^T$. \mathbf{R}_h is covariance matrix noise free and $\mathbf{R}_n = \sigma_n^2 \mathbf{I}$. Assuming that the channel is Wide Sense

Stationary (WSS), we express the cross-correlation by using the Power Spectral Density (PSD), $\mathbf{S}(\omega)$:

$$\begin{aligned} r_h(\tau_{lk}) &= \frac{\sigma_h^2}{2\pi} \int_{\omega_c - \omega_d}^{\omega_c + \omega_d} \mathbf{S}(\omega) \exp(j\omega\tau_{lk}) d\omega \\ &= \sigma_h^2 \exp(j\omega\tau_{lk}) \int_{\omega_d}^{\omega_d} \tilde{\mathbf{S}}(\omega) \exp(j\omega\tau_{lk}) d\omega \end{aligned} \quad (15)$$

where σ_h^2 is the channel variance, $\omega = 2\pi f$, $\omega_c = 2\pi f_c$, $\omega_D = 2\pi\sigma_f$ and $\tau_{lk} = (l - k)T_s$ with l and k are positive integers. Estimating the maximum DS, $\hat{\omega}_D$, remains to estimate $\hat{\sigma}_f$ and estimating $\hat{\omega}_c$ remain to estimate f_c . The proposed approach in [6], is valid only for a symmetric PSD channel and for a small frequency deviation. The second-order Taylor series and the fourth-order expansions are used to approximate the noise free matrix \mathbf{R}_h as follows:

$$\mathbf{R}_h = \sigma_h^2 \int_{-\omega_d}^{\omega_d} \tilde{\mathbf{S}}(\omega) \mathbf{a}(\omega + \omega_c) \mathbf{a}^H(\omega + \omega_c) d\omega, \quad (16)$$

where $\mathbf{a}(\omega) = [1, \exp(j\omega T_s), \dots, \exp(j(N - 1)\omega T_s)]^T$. In [14] and [6], the authors propose to approximate the spatial spread source by two virtual point sources. The application of the second order Taylor series expansions to $\mathbf{a}(\omega)$ in (16) around ω_c provides the following expression of \mathbf{R}_h matrix:

$$\mathbf{R}_h \approx \frac{\sigma_h^2}{2} \mathbf{A}(\omega_c - \sigma_\omega, \omega_c + \sigma_\omega) \mathbf{A}^H(\omega_c - \sigma_\omega, \omega_c + \sigma_\omega), \quad (17)$$

with

$$\mathbf{A}(\omega_c - \sigma_\omega, \omega_c + \sigma_\omega) = [\mathbf{a}(\omega_c - \sigma_\omega) \mathbf{a}(\omega_c + \sigma_\omega)]. \quad (18)$$

We note that the $(l, k)^{th}$ entry of \mathbf{R}_h is defined by $[\mathbf{R}_h]_{lk} = r_h(\tau_{lk})$. Using (14), (17) and (18), $r(\tau_{lk})$ is expressed as:

$$r(\tau_{lk}) \approx \sigma_h^2 \cos(2\pi\tau_{lk}\sigma_f) \exp(j2\pi f_c\tau_{lk}) + \sigma_n^2 \delta(\tau_{lk}). \quad (19)$$

Based on the Toeplitz structure of \mathbf{R} , authors consider the m^{th} entries of the subdiagonal of the matrix \mathbf{R}_{x_i} with $m = (k - l) \in \{-(N - 1) \dots (N - 1)\}$ instead using the double indexing (k, l) as used in [15]. So that $r(\tau_{lk})$ becomes $r(\tau_m)$. In [6] the channel correlation is estimated at different time lags and the matrix \mathbf{R} is computed using the fact that the channel is WSS. We note that for $\tau_m = 0$ ($m = 0$) we obtain $\hat{\mathbf{R}}(0) = (\hat{\sigma}_h^2 + \hat{\sigma}_n^2) \mathbf{I}$. We estimate the noise variance $\hat{\sigma}_n^2$ by averaging over the last smallest eigenvalues of $\hat{\mathbf{R}}$, then we deduce $\hat{\sigma}_h^2$ as:

$$\hat{\sigma}_h^2 = Tr[\hat{\mathbf{R}}(0)] - \hat{\sigma}_n^2. \quad (20)$$

Estimating σ_f and f_c remains to minimize the following cost function using $r(\tau_m)$ with $m > 0$:

$$J^{(m)}(f_c, \sigma_f) = \frac{Tr[\hat{\mathbf{R}}(\tau_m)]}{\sigma_h^2} - \cos(2\pi\tau_m\sigma_f) \exp(j2\pi f_c\tau_m)^2. \quad (21)$$

From (21), we can compute the estimated values of \hat{f}_c and $\hat{\sigma}_f$:

$$\hat{f}_c^{(m)} = \frac{1}{2\pi\tau_m} \angle \text{Tr}[\hat{\mathbf{R}}(\tau_m)]; \quad (22)$$

$$\hat{\sigma}_f^{(m)} = \frac{\arccos(\Re\{\text{Tr}[\hat{\mathbf{R}}(\tau_m)] \exp(-j 2\pi\tau_m \hat{f}_c) / \hat{\sigma}_h^2\})}{2\pi\tau_m} \quad (23)$$

In order to obtain an accurate estimation, authors, in [6], propose to use the smallest positive value of $\tau_m = m T_s$ for estimating f_c and large ones for estimating σ_f . In other terms, authors propose the use of p time lags. Then, the estimates are obtain by averaging as follows:

$$\hat{f}_c^{(m)} = \frac{1}{p} \sum_{m=1}^p \hat{f}_c^{(m)}, \quad (24)$$

$$\hat{\sigma}_f^{(m)} = \frac{1}{p} \sum_{m=1}^p \hat{\sigma}_f^{(m)}. \quad (25)$$

Estimating $\hat{\omega}_D$ needs a *prior* knowledge of the distribution shape. In this work, the Jakes' model [16] is considered with $\omega_D = \sqrt{2} \sigma_\omega = \sqrt{2} 2\pi \sigma_f^{(m)}$. In [6], authors consider $p = 20$ after empirical simulations. We also note that the approximation in (17) and (18) induce a small bias in the $\hat{\sigma}_f$ estimation. Authors propose to induce empirically a correction factor α to overcome this bias, with $\alpha = 1.14$. So the proposed maximum DS estimator becomes:

$$\hat{\sigma}_f^{(m)} = \alpha \hat{\sigma}_f^{(m)}. \quad (26)$$

The Two-Rays approach steps can be summarized in this algorithm:

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| <ul style="list-style-type: none"> (i) Calculate the covariance matrix (14), (ii) Compute the \mathbf{R} matrix, (iii) Estimate $\hat{\sigma}_n^2$ and $\hat{\sigma}_h^2$, (iv) Estimate \hat{f}_c and $\hat{\sigma}_f$ as in (22), (v) Find average estimation of \hat{f}_c and $\hat{\sigma}_f$ as in (24). |
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Table II
MAXIMUM DS ESTIMATOR BASED ON TWO-RAYS APPROXIMATION
ALGORITHM

In Fig 3, we study the effect of the SNR variation on $\hat{\omega}_D$ estimation at different F_D values by taking into account the CFO, we consider f_c at 200Hz. We notice that, the RMSE is insensitive to SNR variation. We also note that, the F_D variation has no effect on the estimation performance.

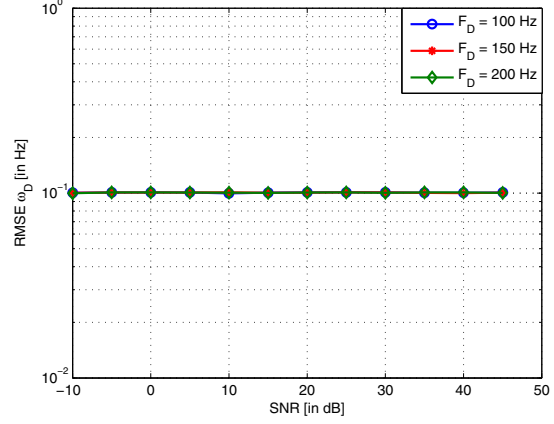


Figure 3. RMSE of $\hat{\omega}_D$ vs SNR

In Fig 4, we study the effect of SNR on \hat{f}_c estimation for different values of F_D . We notice that the \hat{f}_c estimation is insensitive to the SNR variation. We obtain accurate \hat{f}_c estimation, especially for low F_D values. Indeed, the RMSE increases when F_D increases. But the RMSE is relatively small.

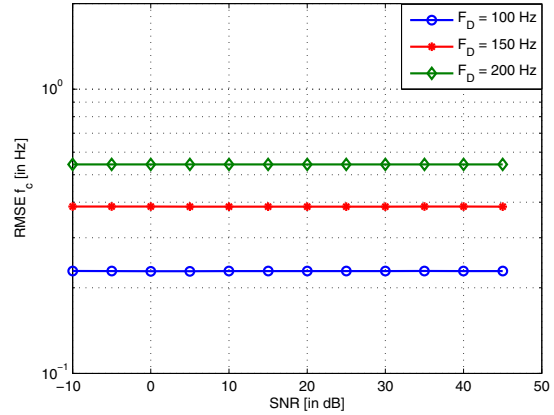


Figure 4. RMSE of \hat{f}_c vs SNR

One can conclude that the estimator based on Two-Rays approximation gives an accurate estimation errors with a low computational complexity. This method does not require a prior knowledge of the angular distribution of the received signal and consider the estimation of the CFO.

V. ITFD-BASED ESTIMATOR

This estimator is developed by Naseh and Azemi in [10], they consider a reduced ITFD of the received signal for estimating the maximum DS. In [13], the same authors proposed a similar maximum DS estimator. We note that the two papers treat the same idea. In fact, the first uses the ambiguity function and the second the reduced ITFD. We prefer the second approach [10] which present better results. We recall that the n^{th} component of the received signal is expressed as:

$$f_{D,n} = F_D \cos(\theta_n). \quad (27)$$

The considered transmission in [10] is a band pass signal. In our work we consider a different signal model. So to obtain same model we multiply the band pass signal by $2\pi f_c$. In [10], the Von-Mises distribution was chosen to model the scattering distribution of the incoming waves, the PDF is expressed in (3). Estimating the maximum DS remains to find the peak of the Instantaneous Frequency (IF) of the received signal by the use of the Time Frequency Signal Processing (TFSP). The IF of the n^{th} component of the received signal is expressed as:

$$f_{i,n}(t) = \frac{1}{2\pi} \frac{d\phi_n(t)}{dt}, \quad (28)$$

where $\phi_n(t) = 2\pi\{(f_c + f_{D,n})\tau_n - f_{D,n}t\}$ and the derivative of $f_{i,n}(t)$ is giving by:

$$f_{i,n}(t) = -f_{D,n}(t) = -F_D \cos(\theta_n). \quad (29)$$

Using (29), the IF of the received signal ensures the following inequality:

$$|f_i(t)| \leq F_D. \quad (30)$$

The estimation of the maximum DS is then giving by:

$$\rho_x[n, k] = \sum_{l=-M}^M \sum_{m=-M}^M G[nTs - lTs, 2mT] \\ x[lTs + mTs]x^*[lTs - mTs] \exp(-j4\pi \frac{mk}{N}), \quad (31)$$

where k is a deterministic constant, N is the signal length, $M = \frac{[N-1]}{2}$ and $G(n, m)$ is the kernel of the TFD. In [10], three time frequency distributions are proposed: the Rihaczek distribution, the Born-Jordan and the Modified B-distribution are proposed. In this work, we consider the Rihaczek representation, for its accuracy and low complexity. It is giving by the Dirac function: $G(n, m) = \delta[n - m]$. It's known that we get to the TFD maximum, at the IF of the received signal [16]. The ITFD algorithm first determines the TFD of the received signal; then finds the associate peak to estimate the IF. Using the TFD property and (30), the estimation of the maximum DS is giving by the last peak of the TFD of the received signal.

$$\hat{\omega}_D = \arg 2\pi\{\text{last positive peak of } [\rho_x[n, :] - \gamma]\}. \quad (32)$$

To overcome the interference induced by multipath phenomenon, the Reduced Interference Distributions (RIDs) can be used in (32). γ is also induced in the estimator expression as a threshold to reduce the effect of the cross-terms and signal windowing in the TFD of the received signal. γ is chosen as the average of the maximum and minimum values of the computed TFD.

The ITFD estimator steps can be summarized in this algorithm:

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| <ul style="list-style-type: none"> (i) Calculate the TFDs of the received signal as (31), (ii) Find the IF of the received signal, (iii) Compute $\hat{\omega}_D$ as in (32). |
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Table III
MAXIMUM DS ITFD-BASED ESTIMATOR

First we study the effect of k variation on the maximum DS estimator giving in (32) and (31). Second, we propose to analyse the effect of the SNR on the maximum DS estimation.

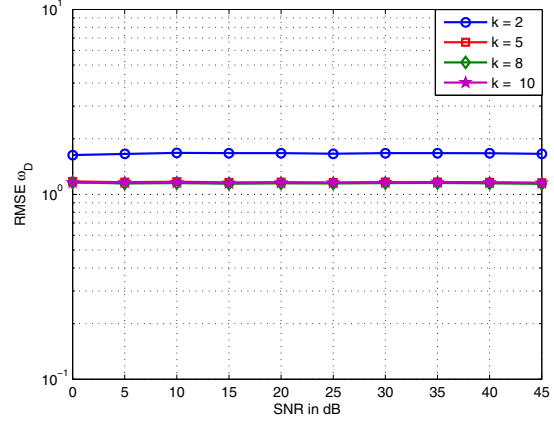


Figure 5. RMSE of $\hat{\omega}_D$ at different k values

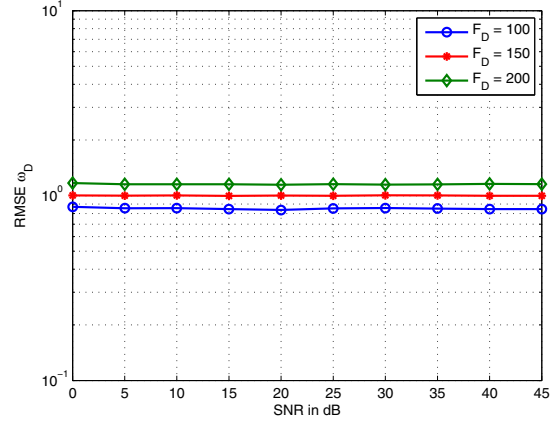


Figure 6. RMSE of \hat{f}_c vs SNR

In Fig 5, we notice that for $k = 10$, we obtain the lowest error. However, for $k = 2$ the RMSE increases. In our simulations, we implement the estimator using reduced ITFD at $k = 10$, for a better accuracy. In Fig 6, we study the effect of the SNR variation for different Doppler frequency values at $k = 10$. As one can notice, the $\hat{\omega}_D$ estimation is insensitive to SNR variation and presents low RMSEs, especially for low F_D values.

One can conclude that the estimator using reduced ITFD gives a reasonable error estimation. This method presents a higher complexity than the two other studied methods due to the computation of the TFDs of the received signal. However, this method does not require a prior knowledge of the angular distribution of the received signal. In the next section, we compare the performances of the three studied estimators.

VI. COMPARISON RESULTS

We study the behavior of aforementioned methods by simulations. We denote the estimator based on correlation function

by ACF, the Two-Rays estimator by TRA. The ITFD-based estimator is denoted by ITFD. For the latter, we consider $k = 10$. We consider 1024 samples and 100 Monte Carlo runs.

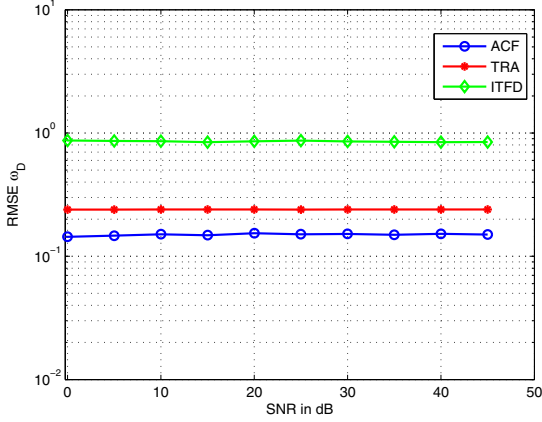


Figure 7. Estimators comparison: RMSE ($\hat{\omega}_D$) at $F_D = 100$

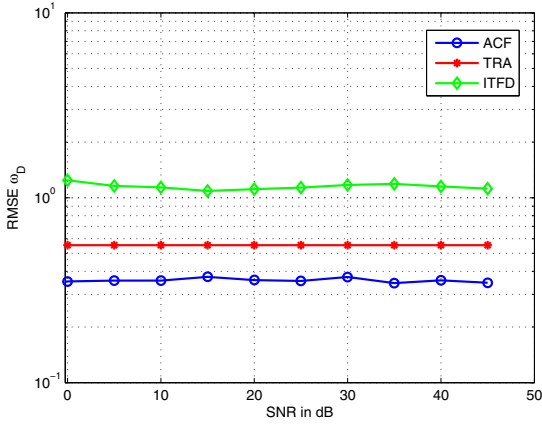


Figure 8. Estimators comparison: RMSE ($\hat{\omega}_D$) at $F_D = 200$

In Fig 7, we study the SNR variation at $F_D = 100Hz$. We notice that, method ACF presents the lowest RMSE results. Moreover, the ITFD method shows high RMSE.

Fig 8 shows the SNR variation at $F_D = 200Hz$. We notice that, the simulation results corroborate with the ones obtained in Fig 7. Indeed, the ACF method present lowest RMSE instead of high RMSE for the ITFD method with small variation due to the SNR. We notice from the comparative figures that the RMSE increase while F_D values increase. For the studied scenarios the ACF method, shows the better accuracy while the ITFD method presents the highest error rate. We also notice that, with TRA method, we obtain an insensitive estimation to SNR and F_D variations. Despite Those methods are low-complexity, the ITFD method shows the highest error of estimation and presents the highest complexity comparing to the two other methods. The simulations results giving by the ACF and TRA methods, have better accuracy than the ones

obtained by the ITFD method. Taking into account that the Two Rays estimator consider the CFO, we can conclude that, this estimator present the best compromise between accuracy and computational complexity.

VII. CONCLUSION

In this work, we studied the problem of the maximum DS estimation. We compared the performance of three different approaches. The first studied one is the autocorrelation-based estimator. The second method uses Two-Rays approximation. The third algorithm uses the reduced interference time frequency. Simulation results showed that the Two Rays estimator offers the best compromise between accuracy and computational complexity.

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