Detecting Specular Propagation Paths in the Presence of Distributed Scattering in Angle and Delay Domains

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Abstract— **In this paper, we derive a method for the detection and estimation of specular propagation paths that takes the correlation in both, angle and delay domain, of the distributed scattering into account. The method is based on an iterative procedure that alternates between the estimation of specular paths and of distributed scattering. The computational complexity is reduced compared to deterministic methods, which are based on the estimation of parameters of a large number of specular paths. The results show that the proposed method is able to detect and estimate the propagation parameters of specular paths that have low power, which would not be distinguished from distributed scattering by existing techniques.**

I. Introduction

In channel parameter estimation from channel sounding measurements mainly two types of models have been employed so far. A widely used model approximates the observed radio channel with a large number of discrete (deterministic) waves, see e.g. [1], [2]. The other approach describes the radio channel as a zero-mean circular complex Gaussian process [3], [4]. The first model is well suited to describe dominant concentrated (specular) propagation paths, i.e., paths with a small delay- and angular spread, each contributing significantly to the wave propagation between transmitter (TX) and receiver (RX). The second model is well suited to describe distributed (diffuse) scattering (DDS). It has been shown in [5] that both mechanisms contribute significantly to the wave propagation. In [2] a data model for channel parameter estimation is proposed, which combines these two models. It is shown that an estimator that accounts for both concentrated propagation paths and distributed scattering outperforms estimators that ignore either of the channel components. However, in [2] the estimator is derived assuming that the contribution of the distributed scattering is an i.i.d. process in the angular domain at TX and RX.

An approximate ML estimator has been derived in [6], [7] for channel parameter estimation from channel sounding measurements, which also takes the angular distribution of the distributed scattering component into account. The power-delay profile of the scattering component is modeled using an exponential distribution, which is typically observed in measurement campaigns [8]. The angular power profile is modeled using a mixture of angular von Mises distributions. The mixture distributions are employed in order to estimate the propagation parameters in scattering environments with multiple clusters of scatterers with high fidelity [9]. The von Mises distribution is described in detail in [10]. The estimator is based on a two step procedure that alternates between the estimation of the parameters of the concentrated propagation paths and distributed scattering.

In this paper we propose an approximate ML method for the detection and estimation of specular paths. The estimator is particularly useful for detection of paths that have low power and may not be easily distinguished from distributed scattering by techniques based on deterministic models. The method is based on the estimator derived in [6]. After each iteration of the estimator, a search is performed for the new specular paths using the information of the previously estimated diffuse scattering and specular component. The estimation procedure is based on the maximum likelihood criterion.

While the full search is optimum in the sense that it maximizes likelihood function, it can be computationaly intensive if each specular path is characterized by a relatively large number of parameters. In order to avoid this problem, we derive a computationaly efficient method that is based on serial interference cancellation and sequential parameter estimation. The simulation results show that the proposed method is able to detect and estimate specular paths, even those whose power is lower than the power of the diffuse scattering component itself.

The paper is organized as follows: in Section II we describe the signal model considered throughout the paper. In Section III we describe the parameter estimator for the diffuse scattering component. In Section IV we describe the proposed method for detection of specular paths. Finally, in Section V we present simulation results to assess the performance of the algorithm.

II. Signal Model

Assuming a channel sounding arrangement with M_r antennas at the receiver and M_t antennas at the transmitter, the signal at the receiver in frequency-domain is given by

$$\mathbf{y}(f) = \mathbf{s}(f) + \mathbf{n}_d(f) + \mathbf{n}(f), \tag{1}$$

where $\mathbf{s}(f)$ represents the specular component of the propagation paths, $\mathbf{n}_d(f)$ represents the diffuse scattering component, and $\mathbf{n}(f)$ represents the zero-mean complex Gaussian measurement noise. The specular paths are modeled as

$$\mathbf{s}(f) = \sum_{l=1}^{N_{sp}} \mathbf{s}_l(f) = \sum_{l=1}^{N_{sp}} \gamma_l \mathbf{b}(\varphi_{R,l}, \varphi_{T,l}) e^{-j2\pi f \tau_l} \mathsf{u}(f), \tag{2}$$

where $\mathsf{u}(f)$ is the transmitted signal, γ_l is the complex gain, $\mathbf{b}(\varphi_{R,l}, \varphi_{T,l})$ is the array response to receive azimuth angle $\varphi_{R,l}$ and transmit azimuth angle $\varphi_{T,l}$, and τ_l is the normalized delay for path $l = 1, \ldots, N_{sp}$. The array response is given as a function of the receive and transmit array responses, $\mathbf{b}(\varphi_{R,l})$ and $\mathbf{b}(\varphi_{T,l})$, respectively, as $\mathbf{b}(\varphi_{R,l}, \varphi_{T,l}) = \mathbf{b}(\varphi_{R,l}) \otimes \mathbf{b}(\varphi_{T,l})$, where $\otimes$ denotes the Kronecker product.

The diffuse scattering component (DSC), $\mathbf{n}_d(f)$, is described as

$$\mathbf{n}_d(f) = \mathbf{h}\mathsf{w}(f)\mathsf{u}(f), \tag{3}$$

where the vector $\mathbf{h}$ of dimension $M_r M_t \times 1$ represents the spatial content of the DSC and is a function of the array response, $w(f)$ represents the frequency-dependent content of the DSC. We assume that the excitation signal $u(f)$ is a multi-carrier spread spectrum signal (MCSSS) [2], which is designed such that $u(f)$ is constant over the bandwidth of interest. Hence, (1) can be rewritten as

$$\mathbf{y}(f) = \mathbf{s}(f) + \mathbf{h}\mathsf{w}(f) + \mathbf{n}(f). \tag{4}$$

Let M_f be the number of observed frequency samples. We then define the $M_o \times 1$ vector $\mathcal{Y}$ as

$$\mathcal{Y} = \begin{bmatrix}\mathbf{y}^T(0) & \cdots & \mathbf{y}^T(M_f-1)\end{bmatrix}^T = \overline{\mathbf{s}} + \mathbf{w}\otimes\mathbf{h} + \overline{\mathbf{n}}, \tag{5}$$

where $M_o = M_r M_t M_f$, and

$$\overline{\mathbf{s}} = \begin{bmatrix}\mathbf{s}^T(0) & \dots & \mathbf{s}^T(M_f-1)\end{bmatrix}^T \tag{6}$$

$$\mathbf{w} = \begin{bmatrix}\mathsf{w}(0) & \dots & \mathsf{w}(M_f-1)\end{bmatrix}^T \tag{7}$$

$$\overline{\mathbf{n}} = \begin{bmatrix}\mathbf{n}^T(0) & \dots & \mathbf{n}^T(M_f-1)\end{bmatrix}^T. \tag{8}$$

From (2), $\overline{\mathbf{s}}$ can be written as

$$\overline{\mathbf{s}}(f) = \sum_{l=1}^{N_{sp}} \gamma_l \mathbf{c}(\tau_l) \otimes \mathbf{b}(\varphi_{R,l}, \varphi_{T,l}), \tag{9}$$

where the $M_f \times 1$ vector $\mathbf{c}(\tau_l)$ is defined as

$$\mathbf{c}(\tau_l) = [\exp(-j2\pi 0\tau_l) \quad \cdots \quad \exp(-j2\pi(M_f-1)\tau_l)]^T. \tag{10}$$

Deterministic maximum likelihood estimation techniques such as the SAGE based method in [11] model the received signal as a combination of a large number of discrete waves. Consequently, parameters from each wave must be estimated. Hence, the algorithms experience convergence problems and the estimates contain artifacts due to local maxima in the likelihood function and high dimensionality of the parameter space.

The following assumptions are employed throughout this article:

(a) the process $\mathbf{n}_d(f)$ in (3) is zero-mean complex temporally white circular Gaussian;
(b) the channel can be treated as constant during the time it takes to measure the channel;
(c) $\mathbf{w}$ and $\mathbf{h}$ are uncorrelated, and we assume $E[\mathbf{h}] = 0$ and $E[\mathbf{w}] = 0$;
(d) the additive noise $\overline{\mathbf{n}}$ is an i.i.d. zero-mean circular complex Gaussian process with known covariance matrix, $\mathbf{C}_n = E[\overline{\mathbf{n}}\overline{\mathbf{n}}^H] = \sigma_n^2\mathbf{I}$, and independent of $\mathbf{w}\otimes\mathbf{h}$ and $\overline{\mathbf{s}}$.

Based on the assumptions above, the PDF of the received signal $\mathcal{Y}$ is completely characterized by its mean, $E[\mathcal{Y}] = \overline{\mathbf{s}}$, and its $M_o \times M_o$ covariance matrix

$$\begin{aligned}\mathbf{C}_y &= E[(\mathcal{Y}-\overline{\mathbf{s}})(\mathcal{Y}-\overline{\mathbf{s}})^H] = E[\mathbf{w}\mathbf{w}^H]\otimes E[\mathbf{h}\mathbf{h}^H] + E[\overline{\mathbf{n}}\overline{\mathbf{n}}^H] \\ &= \mathbf{C}_w \otimes \mathbf{C}_h + \sigma_n^2 \mathbf{I},\end{aligned} \tag{11}$$

where $\mathbf{I}$ is the $M_o \times M_o$ identity matrix.

A. Delay and Frequency Domain Characterization

For the delay domain we use the model in [2], which is based on the observation that the power delay profile (PDP) has an exponential decay over time and a base delay which is related to the distance between the transmitter and receiver. The PDP for infinite bandwidth is given by

$$\psi(\tau) = E[|\mathsf{w}(\tau)|^2] = \begin{cases} 0, & \tau < \tau_d' \\ \alpha_1/2, & \tau = \tau_d' \\ \alpha_1 e^{-B_d(\tau-\tau_d')}, & \tau > \tau_d' \end{cases}, \tag{12}$$

where B_d is the coherence bandwidth, α_1 denotes the maximum power, and τ_d' is the base delay.

The sampled version of the correlation function $\mathbf{v}(\boldsymbol{\theta}_w)$, $\boldsymbol{\theta}_w = \{\alpha_1, \beta_d, \tau_d\}$, of dimension $1\times M_f$ is given in frequency-domain as

$$\mathbf{v}(\boldsymbol{\theta}_w) = \frac{\alpha_1}{M_f}\left[\frac{1}{\beta_d} \quad \frac{e^{-j2\pi\tau_d}}{\beta_d + j\frac{2\pi}{M_f}} \quad \cdots \quad \frac{e^{-j2\pi(M_f-1)\tau_d}}{\beta_d + j2\pi\frac{M_f-1}{M_f}}\right], \tag{13}$$

where $\beta_d = B_d/B_m$ is the normalized coherence bandwidth, B_m is the measurement bandwidth, and τ_d is the normalized base delay.

Since the process is stationary, the correlation between components at different frequencies is characterized by $f_1 - f_2$. Hence, the covariance matrix of the diffuse scattering (assuming the received signal is spatially-white) may be modeled as a Toeplitz matrix

$$\mathbf{C}_w = \text{toep}\big(\mathbf{v}(\boldsymbol{\theta}_w), \mathbf{v}(\boldsymbol{\theta}_w)^H\big), \tag{14}$$

where toep$(\mathbf{a}, \mathbf{b}^H)$ denotes a Toeplitz matrix with $\mathbf{a}$ as its first column and $\mathbf{b^H}$ as its first row, with $a_1 = b_1^*$.

B. Angular Domain Characterization

Using the extended Saleh-Valenzuela (SVA) channel model in [3] we can write $E[\mathbf{h}\mathbf{h}^H]$ as a function of the angular parameters. A similar model is obtained in [4] following a different approach that is related to the geometry of the distribution of scatterers. For simplicity, we will limit the discussion to uni-directional estimation, but the results can be naturally extended to the double directional case. We also assume for simplicity that an uniform linear array (ULA) is used at the receiver. Then the correlation at the receiver side is given by

$$\mathbf{C}_{h,m_1m_2}(\boldsymbol{\Theta}_h) = \int_{-\pi}^{\pi} \exp(b_{m_1m_2}\cos(\phi)) f(\phi, \boldsymbol{\Theta}_h) d\phi, \tag{15}$$

where $f(\phi, \boldsymbol{\Theta}_h)$ is any angular PDF of ϕ, characterized by parameters $\boldsymbol{\Theta}_h$, $b_{m_1m_2} = j2\pi d_{m_1m_2}$, and $d_{m_1m_2}$ is the distance between elements m_1 and m_2 in the receive array. An angular PDF must at least satisfy $f(\phi, \boldsymbol{\Theta}_h) = f(\phi + 2\pi k, \boldsymbol{\Theta}_h)\ \forall\ k \in \mathbb{Z}$, with $\phi \in [\phi_0, \phi_0 + 2\pi)$, $\phi_0 \in \mathbb{R}$. Hence, a Gaussian PDF which has an infinite support is not suitable. The von Mises distribution [10] defined in angular domain is more appropriate. It is defined as follows:

$$f(\phi, \boldsymbol{\Theta}_h) = \frac{1}{2\pi I_0(\kappa)} \exp(\kappa\cos(\phi-\mu)), \tag{16}$$

where μ is the symmetry center or "mean angle" and $I_0(\cdot)$ is the modified Bessel function of the first kind of order zero. The parameter κ is related to the variance of the von Mises distribution, i.e. how scattered about the symmetry center the data are. It can be chosen between 0 (isotropic scattering) and ∞ (extremely concentrated).

In channel measurements it is often found that signals are arriving from a number of different clusters, which may lead to multimodal angular PDFs. This can be modeled using a mixture of angular PDFs,

$$f(\phi, \boldsymbol{\Theta}_h) = \sum_{p=1}^{P} \epsilon_p f_p(\phi, \boldsymbol{\theta}_{h,p}), \tag{17}$$

where P is the number of mixture components, $\sum_{p=1}^{P}\epsilon_p = 1$, ϵ_p are unknown mixture proportions, and $f_p(\phi)$ is any valid angular PDF. With this definition of the angular PDF, the angular domain parameters are defined as $\mathbf{\Theta}_h = \{\boldsymbol{\theta}_{h,1}, \ldots, \boldsymbol{\theta}_{h,P}\}$, with $\boldsymbol{\theta}_{h,p} = \{\mu_p, \kappa_p, \epsilon_p\}$, $p = 1, \ldots, P$.

Using (16), the cross correlation in (15) may be written analytically as [4], [9]

$$\mathbf{C}_{h,m_1 m_2}(\mathbf{\Theta}_h) = \sum_{p=1}^{P} \epsilon_p \frac{I_0(\{\kappa_p^2 + b_{m_1 m_2}^2 + 2\kappa_p b_{m_1 m_2} \cos(\mu_l)\}^{\frac{1}{2}})}{I_0(\kappa_p)}. \tag{18}$$

III. Joint Estimation of DSC and Specular Paths

Let us denote by $\mathcal{Y}_m$ the m-th observation of $\mathcal{Y}$, $m = 1, \ldots, M_s$. Assuming $\mathcal{Y}$ is circular complex Gaussian and that the realizations $\mathcal{Y}_m$ are i.i.d., we can write the log-likelihood function as

$$\begin{aligned} L(\mathcal{Y}_1, \ldots, \mathcal{Y}_{M_s}) &= -M_o M_s \log \pi - M_s \log |\mathbf{C}_y| - \\ &- \sum_{m=1}^{M_s} (\mathcal{Y}_m - \overline{\mathbf{s}})^H \mathbf{C}_y^{-1} (\mathcal{Y}_m - \overline{\mathbf{s}}), \end{aligned} \tag{19}$$

where M_s is the number of observations. We will also assume that the noise is circular complex white Gaussian with variance σ_n^2.

Direct optimization of the likelihood function using (11) is not feasible due to the high dimensionality of the matrices involved. In current sounding systems, typical values for M_f and $M_r M_t$ are in the range $M_f = [100, 2000]$, and $M_r M_t = [4, 64]$. But with the rapid development of the channel sounders this values may grow. This leads to a dimension of $\mathbf{C}_y$ ranging from 400×400 to 128000×128000, or even higher.

An estimation method has been proposed in [6], [7] that reduces the computational complexity by using the following iterative procedure:

(1) Optimize for the parameters of the specular components such as azimuth and elevation angle of arrival/departure, time delay, doppler spread etc., using the previously estimated covariance matrix.
(2) Remove the contribution of the specular components from data and optimize for the covariance matrix of the diffuse scattering components plus noise variance.
(3) Repeat the procedure until convergence or a maximum number of iterations is reached.

Step 2 can be further decomposed into two steps:

(2.a) Optimize for the frequency-domain parameters and noise variance.
(2.b) Optimize for the angular-domain parameters, with $\mathbf{C}_w$ as calculated in the previous step.

The further decomposition of step (2) into steps (2.a) and (2.b) is important due to the high dimensionality of the matrices involved. With this two step procedure it is possible to exploit the Toeplitz structure of $\mathbf{C}_w$ for the computation of the approximate ML estimates. Also, the covariance matrix manipulated in step (2.b) is only $\mathbf{C}_h$, which is typically much smaller in dimension than $\mathbf{C}_w$.

In the sequel we will briefly describe the implementation of the estimator. The reader is referred to [6], [7] for its detailed derivation and computationaly efficient implementation.

A. Specular Component

A *prewhitening* transform is applied to the data such that its covariance matrix becomes a constant times the identity matrix [12]. We then define the matrix $\mathbf{U}$, such that

$$\begin{aligned} &E[(\mathbf{U}^{-H}\mathcal{Y} - \mathbf{U}^{-H}\overline{\mathbf{s}})(\mathbf{U}^{-H}\mathcal{Y} - \mathbf{U}^{-H}\overline{\mathbf{s}})^H] \\ &\qquad = \mathbf{U}^{-H}(\mathbf{C}_w \otimes \mathbf{C}_h + \sigma_n^2 \mathbf{I})\mathbf{U}^{-1} = \mathbf{I}. \end{aligned} \tag{20}$$

Therefore, $\mathbf{U}^{-H}\mathcal{Y}$ can be used to estimate the parameters of the specular-alike propagation paths using any well-known algorithm, such as the SAGE based procedure in [1], [11].

A convenient implementation of $\mathbf{U}$ is given by the eigenvalue decomposition of $\mathbf{C}_y$. Define $\mathbf{V}_w$ and $\mathbf{\Lambda}_w$ as the matrices containing the eigenvectors and eigenvalues of $\mathbf{C}_w$, respectively. Define also $\mathbf{V}_h$ and $\mathbf{\Lambda}_h$ as the matrices containing the eigenvectors and eigenvalues of $\mathbf{C}_h$, respectively. We can then write

$$\mathbf{C}_y = (\mathbf{V}_w \otimes \mathbf{V}_h)(\mathbf{\Lambda}_w \otimes \mathbf{\Lambda}_h + \sigma_n^2 \mathbf{I})(\mathbf{V}_w^H \otimes \mathbf{V}_h^H). \tag{21}$$

Hence, $\mathbf{U}^{-H}$ is given by [6]

$$\mathbf{U}^{-H} = (\mathbf{\Lambda}_w \otimes \mathbf{\Lambda}_h + \sigma_n^2 \mathbf{I})^{-1/2}(\mathbf{V}_w^H \otimes \mathbf{V}_h^H). \tag{22}$$

B. Frequency-Domain Parameters

Prior to estimaton of DSC parameters, the specular paths that have been estimated in previous step are removed from the observation, and hence the likelihood function is given by

$$\begin{aligned} L(\mathcal{Y}_1, \ldots, \mathcal{Y}_{M_s}) &= -M_o M_s \log \pi \\ &- M_s \log |\mathbf{C}_y| - \sum_{m=1}^{M_s} \mathcal{Y}_m^H \mathbf{C}_y^{-1} \mathcal{Y}_m. \end{aligned} \tag{23}$$

In [7] it is shown that maximizing the likelihood function given the angular-domain parameters are fixed during the estimation of the frequency-domain parameters is equivalent to maximizing

$$\begin{aligned} L(\overline{\mathcal{Y}}_1, \ldots, \overline{\mathcal{Y}}_{M_s}) \propto & -\sum_{j=1}^{M_o} \log \overline{\boldsymbol{\lambda}}_j - \frac{1}{M_s} \sum_{m=1}^{M_s} \overline{\mathcal{Y}}_m^H (\mathbf{I}_{M_f} \otimes \mathbf{V}_h) \overline{\mathbf{\Lambda}}^{-1} \\ & \cdot (\mathbf{I}_{M_f} \otimes \mathbf{V}_h^H) \overline{\mathcal{Y}}_m. \end{aligned} \tag{24}$$

where

$$\overline{\mathcal{Y}}_m = (\mathbf{I}_{M_f} \otimes \mathbf{\Lambda}_h^{-1/2} \mathbf{V}_h^H) \mathcal{Y}_m, \tag{25}$$

and

$$\overline{\mathbf{\Lambda}} = (\mathbf{\Lambda}_w \otimes \mathbf{I}_{M_r M_t} + \sigma_n^2 \mathbf{I}_{M_f} \otimes \mathbf{\Lambda}_h^{-1}). \tag{26}$$

The ML estimates of $\boldsymbol{\theta}_{wn} = \{\boldsymbol{\theta}_w, \sigma_n^2\} = \{\alpha_1, \beta_d, \tau_d, \sigma_n^2\}$, are those values that maximize the likelihood function in (24).

C. Angular-Domain Parameters

In [7] it is shown that maximizing the likelihood function given the frequency-domain parameters are fixed during the estimation of the angular-domain parameters is equivalent to maximizing

$$\begin{aligned} L(\widetilde{\mathcal{Y}}_1, \ldots, \widetilde{\mathcal{Y}}_{M_s}) \propto & -\sum_{j=1}^{M_o} \log \widetilde{\boldsymbol{\lambda}}_j - \frac{1}{M_s} \sum_{m=1}^{M_s} \widetilde{\mathcal{Y}}_m^H (\mathbf{I}_{M_f} \otimes \mathbf{V}_h) \widetilde{\mathbf{\Lambda}}^{-1} \\ & \cdot (\mathbf{I}_{M_f} \otimes \mathbf{V}_h^H) \widetilde{\mathcal{Y}}_m, \end{aligned} \tag{27}$$

where

$$\widetilde{\mathcal{Y}}_m = (\mathbf{\Lambda}_w^{-1/2} \mathbf{F}^H \otimes \mathbf{I}_{M_r M_t}) \mathcal{Y}_m, \tag{28}$$

and

$$\widetilde{\mathbf{\Lambda}} = (\mathbf{I}_{M_f} \otimes \mathbf{\Lambda}_h + \sigma_n^2 \mathbf{\Lambda}_w^{-1} \otimes \mathbf{I}_{M_r M_t}). \tag{29}$$

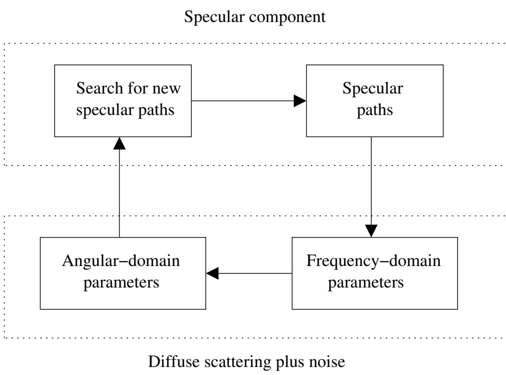

Fig. 1. Iterative procedure for joint optimization of specular component and diffuse scattering parameters, including the search for new specular paths.

IV. Detection and Estimation of Specular Paths

In this section, we propose a procedure for detection and estimation of parameters of specular paths that is based on the estimator described in Section III. The proposed method is particularly useful for the estimation of specular paths with low power, which may not be easily distinguished from distributed scattering by techniques based on deterministic models. Typically, such techniques require a large number of discrete waves to be estimated in order to characterize the channel, and it is not straightforward to identify which of the esimated waves are actual specular paths and which are an attempt to describe the diffuse component. The estimator described in Section III assumes a stochastic model, where the DSC is modeled by a random process. Hence, the specular paths can be easily identified as the deterministic part of the model, while the DSC corresponds to the stochastic part. Moreover, this model requires a reduced set of parameters to be estimated, which usually results in estimates with lower variance. Figure 1 shows how the procedure for searching new paths is inserted into the estimator described in Section III.

The proposed procedure is based on the maximum likelihood estimator for the model described in Section II. We assume that at least one iteration of the estimator described in Section III has been executed. Hence, an estimate of the strongest specular paths is assumed to be available, as well as an estimate of the diffuse scattering component. We estimate the new specular paths following the approach in Section III-A, where the data is multiplied by a whitening transformation. The likelihood function for the whitened signal $\mathcal{Y}' = \mathbf{U}^{-H}\mathcal{Y}$ is given by

$$\begin{aligned} L(\mathcal{Y}'_1,\ldots,\mathcal{Y}'_{M_s}) &\propto -\sum_{m=1}^{M_s}(\mathcal{Y}'_m - \mathbf{U}^{-H}\overline{\mathbf{s}})^H(\mathcal{Y}'_m - \mathbf{U}^{-H}\overline{\mathbf{s}}) \\ &\propto 2\Re\{\sum_{m=1}^{M_s}\overline{\mathbf{s}}^H\mathbf{U}^{-1}\mathcal{Y}'_m\} - \sum_{m=1}^{M_s}\overline{\mathbf{s}}^H\mathbf{U}^{-1}\mathbf{U}^{-H}\overline{\mathbf{s}}. \end{aligned} \tag{30}$$

A serial interference cancellation approach is employed. Hence, we assume the previously estimated concentrated paths have been already removed from data, and that there is only one specular path in $\overline{\mathbf{s}}$ to be detected, with parameters $\boldsymbol{\theta}_s = \{\gamma, \varphi_R, \varphi_T, \tau\}$.

Let us define

$$\mathbf{A}(\tau,\varphi_R,\varphi_T) = (\boldsymbol{\Lambda}_w \otimes \boldsymbol{\Lambda}_h + \sigma_n^2\mathbf{I})^{-\frac{1}{2}}(\mathbf{V}_w^H\mathbf{c}(\tau)\otimes\mathbf{V}_h^H\mathbf{b}(\varphi_R,\varphi_T)). \tag{31}$$

Substituting (9) and (22) in (30), and using the definition in (31), we obtain

$$\begin{aligned} L(\mathbf{U}^{-H}\mathcal{Y}) \propto 2\Re\{\gamma^* \sum_{m=1}^{M_s}\mathbf{A}^H(\tau,\varphi_R,\varphi_T)\mathcal{Y}'_m\} \\ - M_s|\gamma|^2\mathbf{A}^H(\tau,\varphi_R,\varphi_T)\mathbf{A}(\tau,\varphi_R,\varphi_T). \end{aligned} \tag{32}$$

The ML estimates for a single wave are then given by

$$\widehat{\boldsymbol{\theta}_s} = \operatorname{argmax}_{\boldsymbol{\theta}_s} \frac{|\sum_{m=1}^{M_s}\mathbf{A}^H(\tau,\varphi_R,\varphi_T)\mathcal{Y}'_m|^2}{|\mathbf{A}(\tau,\varphi_R,\varphi_T)|^2}, \tag{33}$$

and

$$\widehat{\gamma} = \frac{\sum_{m=1}^{M_s}\mathbf{A}^H(\tau,\varphi_R,\varphi_T)\mathcal{Y}'_m}{M_s|\mathbf{A}(\tau,\varphi_R,\varphi_T)|^2}. \tag{34}$$

Based on the initialization procedure proposed in [1], [11], we can simplify the search in equation (33). First, we estimate the base delay as

$$\widehat{\tau} = \operatorname{argmax}_{\tau} \frac{|\sum_{m=1}^{M_s}\overline{\mathbf{A}}^H(\tau)\mathcal{Y}'_m|^2}{|\overline{\mathbf{A}}(\tau)|^2}, \tag{35}$$

where $\overline{\mathbf{A}}(\tau) = (\mathbf{c}_\tau^H\mathbf{V}_w \otimes \mathbf{1}^H\mathbf{V}_h)(\boldsymbol{\Lambda}_w \otimes \mathbf{1} + \sigma_n^2\mathbf{I})^{-1/2}$, and $\mathbf{1} = [1\cdots1]^T$. With the estimated $\widehat{\tau}$, we estimate the angular parameters as

$$\widehat{\varphi_R} = \operatorname{argmax}_{\varphi_R} \frac{|\sum_{m=1}^{M_s}\mathbf{A}^H(\widehat{\tau},\varphi_R,\varphi_T)\mathcal{Y}'_m|^2}{|\mathbf{A}(\widehat{\tau},\varphi_R,\varphi_T)|^2}, \tag{36}$$

and

$$\widehat{\varphi_T} = \operatorname{argmax}_{\varphi_T} \frac{|\sum_{m=1}^{M_s}\mathbf{A}^H(\widehat{\tau},\widehat{\varphi_R},\varphi_T)\mathcal{Y}'_m|^2}{|\mathbf{A}(\widehat{\tau},\widehat{\varphi_R},\varphi_T)|^2}. \tag{37}$$

The main advantage of this approach is that only 1-D searches are performed, hence reducing the computational complexity. However, the 1-D searches are suboptimal, and the detection performance is reduced compared to the full search.

V. Simulation Results

In this Section simulations examples are presented in order to illustrate the performance of the described parameter estimation procedure. The receiver is equipped with an ULA having $M_r = 8$ antennas and the transmitter uses $M_t = 1$ antenna. The number of frequency points is $M_f = 128$, and the number of channel realizations is $M_s = 5$. For the frequency-domain parameters, typical values often observed in channel sounding experiments are used: $\sigma_n^2 = 0.1$, $\alpha_1 = 1$, $\beta = 0.07$, and $\tau = 0.1$. The angular-domain parameters are defined as $\phi = \{60°, 120°\}$, $\kappa = \{10, 50\}$, $\epsilon = \{0.4, 0.6\}$, corresponding to two clusters in the angular domain.

Two specular paths are present, and modeled as

$$\mathbf{s}(k) = \sum_{l=0}^{1}\gamma_l\mathbf{b}(\varphi_l)\exp(-j2\pi k\tau_l), \tag{38}$$

where γ_l is the complex gain, $\mathbf{b}(\varphi_l)$ is the steering vector for receive azimuth angle φ_l, and τ_l is the normalized delay. For the simulation, the values are set as $\gamma_l = \{0.2e^{j*\pi/5}, 0.02e^{j*\pi/3}\}$, $\varphi_l = \{80°, 150°\}$, and $\tau_l = \{0.12, 0.42\}$.

The received signal is generated as

$$\mathbf{y}(k) = \mathbf{s}(k) + \mathbf{R}^{1/2}\mathbf{n}_2(k) + \mathbf{n}(k), \tag{39}$$

where $\mathbf{n}_2(k)$ is a circular complex white Gaussian process and $\mathbf{R}^{1/2}$ is obtained by, e.g., the Cholesky decomposition of $\mathbf{C}_w \otimes \mathbf{C}_h$. This implies that the covariance matrix of $\mathbf{R}^{1/2}\mathbf{n}_2(k)$ is

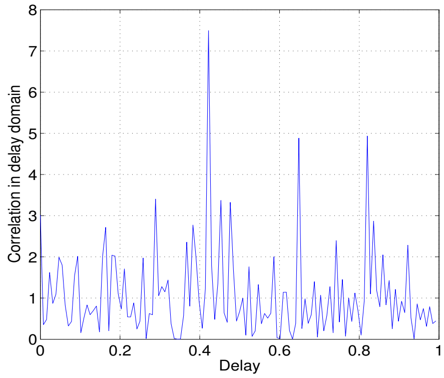

Fig. 2. Output of the 1-D correlation for the estimate of τ. The strongest specular path can be identified.

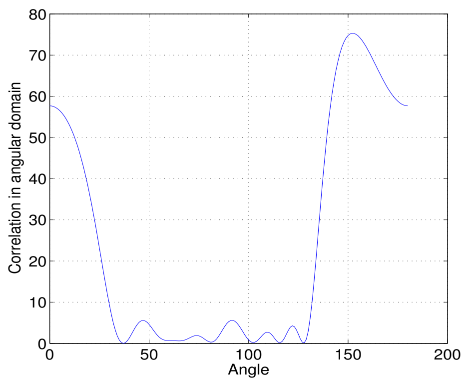

Fig. 3. Output of the 1-D correlation for the estimate of φ, using previously estimated $\hat{\tau}$.

given by $\mathbf{C}_w \otimes \mathbf{C}_h$. The vector $\mathbf{n}(k)$ is a circular complex white Gaussian process representing the measurement noise.

Figures 2 and 3 show the output of the 1-D correlations in (35) and (36). The second specular path can be clearly identified and its parameters can be estimated. Finally, Figures 4 and 5 show the power delay profile (PDP) and power angular profile (PAP) obtained using the estimation procedure described in this article, and compares them to the actual PDP and PAP, respectively. The curves overlap almost perfectly.

VI. Conclusions

In this paper, we derive a method for the detection and estimation of specular propagation paths that takes the correlation in both, angle and delay domain, of the distributed scattering into account. The method is based on an iterative procedure that alternates between the estimation of specular paths and of distributed scattering. After each iteration, a search is employed to detect specular paths that had not been observed before. The search is based on serial interference cancellation, and the strongest specular paths are estimated and removed from data.

The simulations show that the method is able to detect and estimate properly waves that are difficult to detect using estimators based on deterministic models. We also show that the method is able to estimate concentrated paths with low power, which are unlikely to be detected by estimators that take only the frequency domain correlation of the diffuse scattering into account.

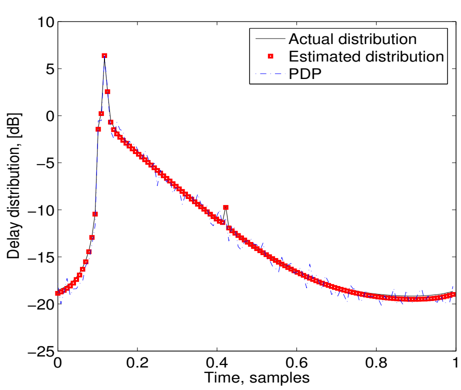

Fig. 4. Comparison of estimated power delay profile and actual power delay profile. The curves overlap almost perfectly.

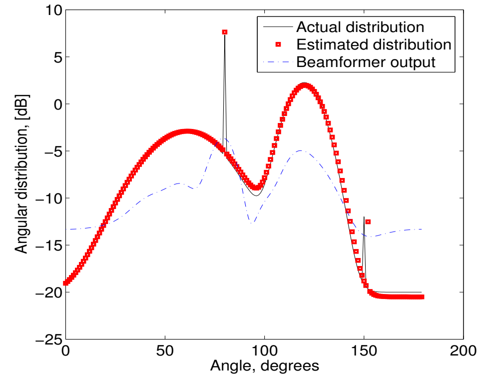

Fig. 5. Comparison of estimated power angular profile and actual power angular profile. The curves overlap almost perfectly. Also shown is the output of the Bartlett beamformer.

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