RECENT ADVANCES IN RADIO CHANNEL PARAMETER ESTIMATION FROM CHANNEL SOUNDING MEASUREMENTS

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Abstract

In this paper we address the problem of parametric channel estimation in channel sounding. In the first part we will give an overview of radio channel data models developed in recent years. Most commonly used parametric radio channel estimation techniques employ a deterministic data model based on a finite number of specular propagation paths only. However, it has been shown, that this data model may not sufficiently describe radio channel observations. The channel model has also to account for diffuse scattering in the channel. We will outline a means to include local and distributed scattering in the channel model. In the second part, a short survey of estimation techniques developed to determine the related model parameters is given.

I. INTRODUCTION

The interest in the multidimensional structure of the mobile radio channel is growing rapidly. This is mainly due to the fact that future beyond 3G wireless systems will employ multi-antenna transceivers in order to improve spectral efficiency and radio link quality. Consequently, realistic channel models that are verified by real-world measurement campaigns are needed especially for transceiver design and network planning purposes. Channel sounding and related propagation parameter estimation are key tasks in creating such channel models. In particular, the double-directional modeling of the radio channel has attracted a lot of interest because it gives a better physical insight into the wave propagation mechanism in real radio environments. Furthermore, propagation parameter estimation is crucial important for network planning.

In the first part of the paper we give an overview of radio channel data models developed in recent years. In the second part, a short survey of estimation techniques developed to determine the related model parameters is given.

II. DATA MODEL FOR A CHANNEL OBSERVATION

Most commonly used parametric radio channel estimation techniques employ a data model based on a finite number of specular propagation paths only. However, it has been shown, for example in [1] that this data model is not sufficient to describe radio channel observations. The fundamental problem is that the propagation between transmitter and receiver has also a significant diffuse scattering component. Theoretically, the non-specular components of an observed channel impulse response can be approximated by a large amount of weak propagation paths. However, this data model is not suitable for parametric channel estimation since the number of unknowns grows with the number of propagation paths. Consequently, the parameter estimation problem for the resulting data model may be ill-posed or even underdetermined.

Three approaches have been published so far to overcome the shortcomings of the data model. The so called GAM (generalized array manifold) model uses a generalized model for a propagation path, which can account for a small angular-, Delay- and Doppler-spread of a propagation path [2]. It is a means to describe local diffuse scattering. Another approach [1] describes the contribution of diffuse scattering to radio propagation by a circular Gaussian process having an exponential decay in the time-delay domain and beeing uncorrelated between the antenna elements. It allows to model distributed diffuse scattering. Finally, in [3] a mixture of von Mises distributions is used to model the channel. The von Mises distribution is suitable for directional data defined in the angular domain using only few parameters. This data model is flexible since it can account for propagation paths having a small spread (local scattering) as well as distributed diffuse scattering, i.e., a heavy tailed distribution. All channel model components, outlined in the subsequent sections, use the base-band representation to express the radio channel.

A. Model for Specular Propagation Paths

The commonly used data model for specular propagation paths is based on the assumption that each path can be described as a R_p-dimensional (5-D) shift operator on the transmit signal. It shifts the Tx-signal in the 4 independent angular domains, i.e., transmit azimuth φ_T and elevation ϑ_T, receive azimuth φ_R and elevation ϑ_R, as well as in the time-delay domain τ. For notational convenience we replace the shift-parameters of propagation path (component) p from the physical model using normalized shift parameters $\mu_p^{(r)}$, which are related to their physical counterparts $\varphi_{T,p}$, $\vartheta_{T,p}$, $\varphi_{R,p}$, $\vartheta_{R,p}$, and τ_p by a unique projection.

A channel sounder uses a band limited periodic wideband signal at a carrier frequency f_c to excite the radio channel. Commonly used excitation signals are MCSSS (multicarrier spread spectrum signal) and PN-sequences (pseudo-noise sequences). Consequently, a channel sounder samples the radio channel at $M_f = B_m T_{seq}$ frequency points, where B_m denotes the measurement bandwidth and T_{seq} the period of the excitation signal. The normalized time delay is defined as

$$\mu^{(1)} = 2\pi \frac{\tau}{T_{seq}}.$$

Now we introduce antenna arrays at the transmitter and the receiver in order to aquire information about the direction of the propagation path at both ends of the link. We assume that the direction of departure (DoD) is given by the parameter pair $(\mu^{(2)}, \mu^{(3)})$ and the direction of arrival (DoA) is determined by $(\mu^{(4)}, \mu^{(5)})$. Furthermore, we assume the number of antenna elements in the transmit and receive array is M_T and M_R, respectively. The related antenna array response vectors are $\mathbf{b}_{\mathrm{T}}(\mu^{(2)}, \mu^{(3)}) \in \mathbb{C}^{M_T \times 1}$ and $\mathbf{b}_{\mathrm{R}}(\mu^{(4)}, \mu^{(5)}) \in \mathbb{C}^{M_R \times 1}$, respectively. Alltogether, we aquire a total of $M = M_f M_T M_R$ complex samples with the outlined channel sounding configuration. If we stack the $M_T \times M_R$ measured channel transfer functions into a vector we can describe a propagation path by

$$\mathbf{s}_p = \mathbf{b}_{\mathrm{R}}(\mu^{(4)}, \mu^{(5)}) \otimes \mathbf{b}_{\mathrm{T}}(\mu^{(2)}, \mu^{(3)}) \otimes \mathbf{b}_f(\mu^{(1)})\gamma,$$

where $\otimes$ denotes the Kronecker-product, and γ is the complex path weight.

The outlined data model for one propagation path can easily be extended to describe P propagation paths. We define three matrices where we collect the individual channel transfer functions (1), transmit array responses (2) and receive array responses (3) for all P propagation paths, as follows:

$$\mathbf{B}_f = \left[\mathbf{b}_f\left(\mu_1^{(1)}\right) \cdots \mathbf{b}_f\left(\mu_P^{(1)}\right)\right] \in \mathbb{C}^{M_f \times P}, \tag{1}$$

$$\mathbf{B}_T = \left[\mathbf{b}_{\mathrm{T}}\left(\mu_1^{(2)}, \mu_1^{(3)}\right) \cdots \mathbf{b}_{\mathrm{T}}\left(\mu_P^{(2)}, \mu_P^{(3)}\right)\right] \in \mathbb{C}^{M_T \times P}, \tag{2}$$

and

$$\mathbf{B}_R = \left[\mathbf{b}_{\mathrm{R}}\left(\mu_1^{(4)}, \mu_1^{(5)}\right) \cdots \mathbf{b}_{\mathrm{R}}\left(\mu_P^{(4)}, \mu_P^{(5)}\right)\right] \in \mathbb{C}^{M_T \times P}. \tag{3}$$

A radio channel containing P specular propagation paths can be expressed by the superposition of the individual propagation paths, i.e.,

$$\mathbf{s} = \left(\mathbf{B}_R \diamond \mathbf{B}_T \diamond \mathbf{B}_f\right)\boldsymbol{\gamma}, \tag{4}$$

where $\diamond$ denotes the Khatri-Rao product (column-wise Kronecker-product) and $\boldsymbol{\gamma} \in \mathbb{C}^{P \times 1}$ a column vector containing all P complex path weights

$$\boldsymbol{\gamma} = \left[\gamma_1 \cdots \gamma_P\right]^{\mathrm{T}}.$$

Since the Khatri-Rao product $\mathbf{B} = \mathbf{B}_R \diamond \mathbf{B}_T \diamond \mathbf{B}_f$ in (4) describes the structure of the radio channel, we call the related parameters $\mu^{(i)}$ also structural parameters. Let us introduce a parameter vector $\boldsymbol{\mu}$ containing all structural parameters and write

$$\mathbf{B}\left(\boldsymbol{\mu}\right) = \mathbf{B}$$

to state this relationship explicitely. Furthermore, we introduce a parameter vector containing all the parameters of the specular propagation paths

$$\boldsymbol{\theta} = \left[\begin{array}{ccc} \boldsymbol{\mu}^{\mathrm{T}} & \Re\{\boldsymbol{\gamma}\}^{\mathrm{T}} & \Im\{\boldsymbol{\gamma}\}^{\mathrm{T}} \end{array}\right]^{\mathrm{T}}, \tag{5}$$

where $\Re\{\bullet\}$ denotes the real part and $\Im\{\bullet\}$ the imaginary part. We may write

$$\mathbf{s}\left(\boldsymbol{\theta}\right) = \mathbf{s}$$

to state explicitely that $\mathbf{s}(\boldsymbol{\theta})$ is a function mapping the propagation path parameters to the observation, i.e., $\boldsymbol{\theta} \in \mathbb{R}^{LP \times 1} \Rightarrow \mathbf{s} \in \mathbb{C}^{\mathbf{M} \times \mathbf{1}}$, where L is the number of parameters used to parameterize a propagation path. The outlined data model is based on the assumption that the radio channel contains only specular reflection or scatterers having a very small spread, i.e., scatterers with a spread which is not observable within the resolution of the measurement system used to observe the channel. In the next section, this model is extended to account for scatterers having a small but observable spread.

B. Model for Slightly Distributed Scatterers (SDS)

In [4] the application of the GAM model (Generalized Array Manifold) [2] for SDS (Slightly Distributed Scatterers] has been proposed. The GAM uses the Taylor-series expansion of the array response, e.g. of $\mathbf{B}_R$ to describe the spread of a scatterer. For example, the model (4) can be extended to account for a small angular spread at the receiver using

$$\mathbf{s} = \left[\begin{array}{ccc} \left(\mathbf{B}_R \diamond \mathbf{B}_T \diamond \mathbf{B}_f\right) & \left(\frac{\partial}{\partial\mu^{(4)}}\mathbf{B}_R \diamond \mathbf{B}_T \diamond \mathbf{B}_f\right) & \left(\frac{\partial}{\partial\mu^{(5)}}\mathbf{B}_R \diamond \mathbf{B}_T \diamond \mathbf{B}_f\right) \end{array}\right] \cdot \left[\begin{array}{c} \boldsymbol{\gamma} \\ \boldsymbol{\gamma}_{\boldsymbol{\mu}^{(4)}} \\ \boldsymbol{\gamma}_{\boldsymbol{\mu}^{(5)}} \end{array}\right], \tag{6}$$

where the parameters $\boldsymbol{\gamma}_{\mu^{(4)}}$ and $\boldsymbol{\gamma}_{\mu^{(5)}}$ contain the spread in azimuth and elevation, respectively. The related parameter vector is given by

$$\boldsymbol{\theta} = \left[\begin{array}{ccccccc} \boldsymbol{\mu}^{\mathrm{T}} & \Re\{\boldsymbol{\gamma}\}^{\mathrm{T}} & \Im\{\boldsymbol{\gamma}\}^{\mathrm{T}} & \Re\{\boldsymbol{\gamma}_{\mu^{(4)}}\}^{\mathrm{T}} & \Im\{\boldsymbol{\gamma}_{\mu^{(4)}}\}^{\mathrm{T}} & \Re\{\boldsymbol{\gamma}_{\mu^{(5)}}\}^{\mathrm{T}} & \Im\{\boldsymbol{\gamma}_{\mu^{(5)}}\}^{\mathrm{T}} \end{array}\right]^{\mathrm{T}}. \tag{7}$$

In the same way, the data model for the specular paths can be extended to account for a small spread in time-delay and/or for some angular spread at the transmitter. As already mentioned before the SDS model can only account for a small spread of a scatterer, i.e., the scatterer has to be small enough such that the first order Taylor-series expansion of the data model is sufficient to describe the spread.

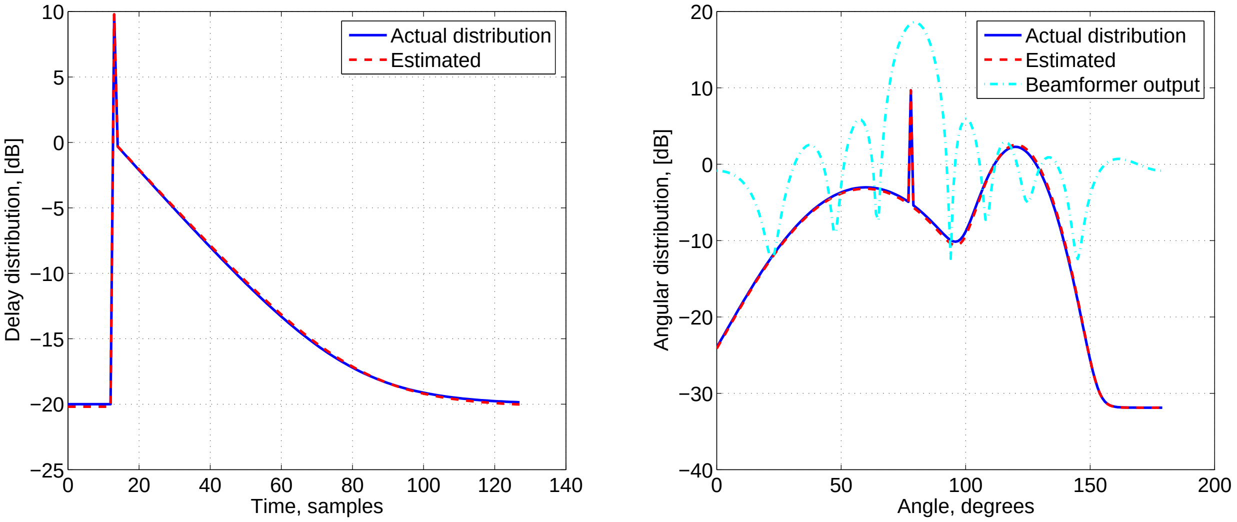

Fig. 1. Comparison of an estimated power delay profile and actual power delay profile (LHS), and an estimated power angular profile and actual power angular profile (RHS). Also shown in the figure on the (RHS) is the output of a Bartlett beamformer.

C. *Model for Dense Multipath Components in the Time Delay Domain*

In [1] it is shown, that the observed radio channel consists not only of specular components but also of dense multipath components (DMC). Hence, we approximate the radio channel observation $\mathbf{y} \in \mathbb{C}^{M \times 1}$ with the superposition of a finite number P of specular propagation paths and the realization of a stochastic process describing DMC and measurement noise. We assume that the complex vector $\mathbf{n}_d$, describing the distribution of the observed dense multipath components, is drawn from a multivariate circular Gaussian process $\mathcal{N}_c\left(\mathbf{0}, \mathbf{R}_d\right) \in \mathbb{C}^{M \times 1}$. Furthermore, we model the measurement noise by a zero mean circular Gaussian process $\mathbf{n}_m \sim \mathcal{N}_c\left(\mathbf{0}, \sigma^2 \mathbf{I}\right) \in \mathbb{C}^{M \times 1}$, where σ^2 denotes the noise variance. The complete model for a channel observation is given by

$$\mathbf{y} = \mathbf{s}\left(\boldsymbol{\theta}\right) + \mathbf{n}_d + \mathbf{n}_m. \tag{8}$$

For a discussion about the structure of the covariance matrix $\mathbf{R}_d$ of the process $\mathbf{n}_d$, see [1]. From the parameter estimation point of view it is reasonable to combine the independent circular Gaussian processes $\mathbf{n}_d$ and $\mathbf{n}_m$ into one process yielding $\mathbf{n}_y = \mathbf{n}_d + \mathbf{n}_m$. The covariance matrix of the process $\mathbf{n}_y$ is $\mathbf{R}_y = \mathbf{R}_d + \sigma^2 \mathbf{I}$. Consequently, the expression for a channel observation (8) reduces to

$$\mathbf{y} = \mathbf{s}\left(\boldsymbol{\theta}\right) + \mathbf{n}_y. \tag{9}$$

D. *Model for Dense Multipath Components in the Angular Domain*

The model described in [1] accounts only for the distribution of the dense multipath components in the time-delay domain. An approach to describe the distribution of dense multipath components in the angular domain has been proposed in [3]. The model approximates the distribution of the DMC in the angular domain by a mixture of von Mises distributions. It can handle arbitrary clustering of scatterers. The model can be combined with the model describing the distribution of the DMC in the time-delay domain. The model combining both components is also described in [3].

Figure 1 shows an example of the power-angular and power-delay profile of a channel model combining a specular propagation path and the contribution of dense multipath components. The dense multipath components are described by a mixture of two von Mises distributions in the angular domain.

E. *Summary on Channel Observation Models*

One should observe that the aforementioned data models are not mutually exclusive, they rather complement each other. However, with the refinement of the data model the complexity of the parameter estimators is growing. Furthermore, with the growing number of candidate channel model components the selection of the optimal model for a given channel observation is a new challenge. One has to solve a model selection problem and not only a model order selection problem as it arises if the channel is modelled using specular propagation paths.

III. MODELLING THE TIME VARYING CHANNEL PARAMETERS

The components of the data model outlined so far, can be used to describe a single channel observation. Another line of research aims at modelling the behavior of the radio channel parameters in time. The idea is to describe the evolution of parameters such as time-delay of arrival, angles of departure, angles of arrival, and Doppler shift in time by appropriate deterministic functions and/or distributions. The dependency of the channel parameters in time can be exploited by the channel estimator to improve the estimates and is also of interest for channel modelling. To the best of our knowledge, two models have been proposed to describe the evolution of the channel parameters in time. The authors of [5] propose to model the evolution of these parameters by a deterministic linear model. The authors of [6] use a state space model to describe the dynamics of the structural parameters in time. The approach used in [5] assumes a picewise linear change of the structural parameters $\boldsymbol{\mu}$

in time and treats the weight parameters $\boldsymbol{\gamma}$ as independent in time. Consequently, the data model for a sequence of K channel observations is given by $\mathbf{S} = \left[\mathbf{s}\left(\boldsymbol{\theta}_{\mathbf{0}}\right) \cdots \mathbf{s}\left(\boldsymbol{\theta}_{(\mathbf{K-1})}\right)\right] \in \mathbb{C}^{M \times K}$, where $\mathbf{s}\left(\boldsymbol{\theta}_{\mathbf{k}}\right)$ is defined in equ. (4), having parameter vector $\boldsymbol{\theta}_{\mathbf{k}} = \left[\boldsymbol{\mu}_{\mathbf{k}}{}^T \boldsymbol{\gamma}_{\mathbf{k}}{}^T\right]^T$ with $k = 0, \ldots, (K-1)$. The evolution of the structural parameters $\boldsymbol{\mu}_k$ is modelled as

$$\boldsymbol{\mu}_k = \boldsymbol{\mu}_0 + k \cdot \Delta\boldsymbol{\mu}, k = 1, \ldots, (K-1)\,. \tag{10}$$

One of the main drawbacks of this model is its complexity. The amount of data to be process at one time is proportional to $M \times K$. To avoid this problem the state space model outlined in [6] has been developed.

The state vector $\boldsymbol{\theta}_k$ is given by equation (5) and has the dimension $LP \times 1$, where L is the number of parameters of interest and P is the number of propagation paths. The state space model may be written as:

$$\begin{aligned} \boldsymbol{\theta}_{k+1} &= \boldsymbol{\Phi}\boldsymbol{\theta}_k + \mathbf{v}_k \\ \mathbf{y}_k &= \mathbf{s}\left(\boldsymbol{\theta}_k\right) + \mathbf{n}_{y,k}, \end{aligned} \tag{11}$$

where the nonlinearity $\mathbf{s}\left(\boldsymbol{\theta}_k\right)$ is mapping the state vector $\boldsymbol{\theta}_k$ to the observation vector $\mathbf{y}_k$ of dimension $M \times 1$. All the entries in the state vector are uncorrelated with each other. This means that they evolve independently in time which leads to a diagonal structure of the state transition matrix $\boldsymbol{\Phi}$. The spectral radius of $\boldsymbol{\Phi}$ is assumed to be less than unity to ensure stability.

The state noise is additive real white Gaussian while the observation noise is circular complex white Gaussian. The state and observation noise sequences are assumed to be uncorrelated with each other and uncorrelated with the state. The covariance matrix of the state noise is given by $\mathbf{Q}_{\boldsymbol{\theta}}$ and is a diagonal matrix containing the noise variance of each parameter on the diagonal. The advantage of the state space model is, that it allows the processing of channel measurement data observation by observation. That means the amount of data to be processed at one time is proportional to $M \times 1$. Consequently, an estimator using the state space model has to process the same amount of measurement data processed by an estimator ignoring the time evolution of the channel parameters.

IV. CHANNEL PARAMETER ESTIMATION

Commonly, subspace-based parameter estimation algorithms such as multidimensional Unitary ESPRIT [7] and RARE [7] as well as maximum likelihood estimators [8] have been applied to estimate the model parameters. The applicability of multidimensional Unitary ESPRIT and RARE is restricted, since they require that the radio channel is observed with uniform linear arrays or uniform rectangular arrays. Furthermore, the joint estimation of specular paths and DMC is not possible using this estimators. For a discussion on the applicability of subspace based methods to channel parameter estimation see [1].

Since the aforementioned state-of-the-art data models are very complex, mainly maximum-likelihood based estimators are used nowadays. Due to the high complexity of the data model the full search over all parameter dimensions, i.e., the straight forward implementation of the maximum likelihood principle, is computationally too expensive. Furthermore, a closed form solution to estimate the channel parameters from channel observations does not exist in general.

Therefore, the space alternating expectation maximization algorithm (SAGE) has been applied to reduce the complexity [8]. However, it has been shown in [1] that the brute force application of the SAGE principle may lead to a significant reduction in convergence speed. One has to take the coupling between model parameters into account when dividing the whole parameter estimation problem into subproblems. In [1] the combination of the SAGE algorithm with well known local optimization strategies such as iterative maximum likelihood is proposed to assure fast convergence of the estimation algorithm. In the same work an approach for joint estimation of DMC parameters in the time-delay domain and specular propagation paths is described.

Based on this approach an algorithm has been developed in [3], which estimates the parameters of specular propagation paths and the time-delay distribution as well as the angular distribution of DMC. In this work the distribution of the DMC in the angular domain is modelled using the von Mises distribution.

In [4] an SAGE based algorithm is described, which estimates the parameters of the aforementioned SDS model from channel sounding measurements. The proposed estimator does not account for distributed diffuse scattering components of the radio channel.

In [5] the algorithm developed in [1] has been extended to estimate also the time variation of the propagation path parameters based on the linear model (10). In [6] the EKF (extended Kalman filter) is applied to estimate the state space model (11) describing the time evolution of the specular propagation paths. For the estimation of the DMC parameters the maximum likelihood based algorithm, developed in [1], has been employed. The new algorithm based on the EKF provides not only additional information about the time evolution of the propagation parameters it is also a means to reduce the computational complexity.

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