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RIMAX - A Flexible Algorithm for Channel Parameter Estimation from Channel Sounding Measurements

Andreas Richter
Technische Universität Ilmenau
FG EMT
POB 100565
98684 Ilmenau
GERMANY
Phone: + 49-3677 69 1160
Fax: + 49-3677 69 1113
Email: ric@e-technik.tu-ilmenau.de

RIMAX - A Flexible Algorithm for Channel Parameter Estimation from Channel Sounding Measurements

Andreas Richter, Markus Landmann, Reiner S. Thomä

Ilmenau University of Technology, Ilmenau, Germany
ric@e-technik.tu-ilmenau.de

Abstract -- We propose a flexible framework for multidimensional maximum likelihood channel parameter estimation from polarimetric channel sounding measurements. The proposed algorithm allows the joint estimation of the parameters of the specular paths and the distributed diffuse scatterers. Depending on the available measurements, the algorithm estimates the four coefficients of the polarimetric path weight matrix, the azimuth and elevation at the TX-site, azimuth and elevation at the Rx-site, the path delay, and the Doppler-shift of the specular components. We outline the main steps of the algorithm and present parameter estimation results from channel sounding measurements.

I. Introduction

The interest in the multidimensional structure of the mobile radio channel is growing rapidly. The initial motivation was the investigation of the space-time structure at the base station (BS). In the recent time the double-directional modeling of the radio channel has attracted a lot of interest [1]. This is mainly due to two reasons. At one hand, double directional channel measurements gives a better physical insight into the wave propagation mechanism in real radio environments since it provides an enhanced multi-path resolution and has the ability to remove the measurement antenna influence from the channel observation [2]. There is, on the other hand, a growing interest in the exploitation of multiple antennas at both the BS and MS site. These MIMO (multiple-input-multiple-output) transmission systems promise a considerable increase in capacity [3]. Parametric MIMO channel models are required not only to estimate the achievable capacity from measurements [4] but also for realistic link-level simulations [5], [6] and to predict the long term channel parameters for controlling of the modem signal processing at the down-link.

Since resolution and accuracy of classical signal processing algorithms is limited by the available measurement aperture in the space-frequency-time domain, parametric super-resolution algorithms are applied to enhance the resolution by fitting an appropriate data model to the measured data. The achievable resolution is only limited by the signal to noise ratio (SNR), the remaining measurement device calibration error, and the limited validity of the data model. The algorithms applied to joint multidimensional radio channel parameter estimation from field experiments so far are the multidimensional ESPRIT (Estimation of Signal Parameters via Rotational Invariance Techniques) algorithm [7], and the SAGE (Space Alternating Generalized Expectation maximization) method [8] which, essentially, is an EM-based simplified ML parameter estimation procedure whereby the parameters are updated sequentially. Both algorithms have been applied to the problem [9], [10], [11], [12], [13], [14]. Important differences between the two algorithms to be considered are their applicability to certain antenna array architectures, calculation time in terms of convergence speed and statistical efficiency. It is well known that the ESPRIT-algorithm is an unbiased estimator for direction estimation only if the antenna arrays used for the measurements show a so called shift invariant structure (ULA, URA, CUBA) [7], [12], [14]. For other antenna array structures, i.e.

UCA, UCPA, or spherical arrays, ESPRIT application is not possible or will at least result in biased estimates. Other drawbacks arise if we ask for a statistically efficient estimator and/or for the parameter estimation in a more complicated context such as colored measurement noise, non-ideal antenna-array-characteristics, etc. Therefore, we will focus on maximum likelihood parameter estimation in this paper.

As long as a sufficient accurate continuous parametric data model of the antenna array output signal is available, SAGE based channel parameter estimation can be applied for a large variety of antenna array architectures. The drawback is its slow convergence rate if two "closely spaced" propagation paths exist in the multi-path propagation scenario. Clearly, since we have only one transmitting source, all received paths have to be considered as potentially coherent. From our experience, this is a serious problem in typical micro- and pico-cell radio environments.

We present in the following Section our general data model for the measured radio channel, and in the third Section an expression for the Fisher information matrix (FIM) of the parameters to be estimated is derived. In Section four we outline our gradient based multidimensional ML channel parameter estimator, and finally, in the last Section we present some concluding remarks.

II. General Data Model

We will use the well known base-band representation of the double directional channel model [1], [12], [14] that approximates the narrow-band radio channel by the superposition of a finite number of propagation paths. Every propagation path is parameterized by 14 real values, the real- and imaginary part of the four polarimetric complex path weights $\gamma_{HH}, \gamma_{HV}, \gamma_{VH}, \gamma_{VV}$, the transmit angles φ_T, ϑ_T (azimuth and elevation), the time-delay τ, the Doppler-shift α, and the receive angles φ_R, ϑ_R (azimuth and elevation).

$$\begin{aligned}\mathbf{h}(\alpha,\tau,\varphi_R,\vartheta_R,\varphi_T,\vartheta_T) = \sum_{k=1}^{K} \begin{bmatrix} \gamma_{HH,k} & \gamma_{HV,k} \\ \gamma_{VH,k} & \gamma_{VV,k} \end{bmatrix} \cdot \delta(\alpha-\alpha_k)\,\delta(\tau-\tau_k)\cdot \\ \cdot\,\delta(\varphi_R-\varphi_{R_k})\,\delta(\vartheta_R-\vartheta_{R_k})\cdot \\ \cdot\,\delta(\varphi_T-\varphi_{T_k})\,\delta(\vartheta_T-\vartheta_{T_k})\end{aligned}$$

It is important to observe that every propagation path can be interpreted as an R-dimensional (6-D) shift operator on the transmit signal. It shifts the Tx-signal in the 4 independent angular domains, in the time-delay domain, and in the Doppler-frequency domain. A second observation important as well is that the 6 related aperture domains frequency, time, and antenna array aperture are finite. The excitation signal is band-limited, the observation time interval is always finite, and the aperture of antenna arrays is limited too. Thirdly the parameters are or can be treated as bounded parameters. All angles are bounded by at least $(-\pi, +\pi)$, the time-delay is bounded by $(0, \tau_{max})$ where τ_{max} is a function of transmit power, free space loss, and receiver noise, and the Doppler-Shift is bounded by $(-\alpha_{max}, +\alpha_{max})$ whereby α_{max} is a function of the maximum velocity of the objects in the observed scenario and the carrier frequency.

Under this terms and considering that a shift in one domain can also be expressed by the multiplication with a complex exponential in the related aperture domain, the family of exponential functions is sufficient to construct a complete data model of the radio channel. For notational convenience we replace the shift-parameters of propagation path (component) k from the physical model using normalized shift parameters $\mu_k^{(i)}$, which are related to their physical counterparts by a unique projection. We collect all parameters $\mu_k^{(i)}$ belonging to one propagation path k in the vector $\boldsymbol{\mu}_k$, and construct the vector-valued basis function for one propagation path using the aperture sizes $N_1 ... N_R$ in the respective domains. Let

$$\mathbf{a}\left(\mu_k^{(i)}\right)=\frac{1}{\sqrt{N_i}}\cdot\left[\mathrm{e}^{-\mathrm{j}\cdot\mu_k^{(i)}\cdot\frac{N_i-1}{2}} \quad \ldots \quad 1 \quad \ldots \quad \mathrm{e}^{+\mathrm{j}\cdot\mu_k^{(i)}\cdot\frac{N_i-1}{2}}\right]^T$$

be the vector valued complex exponential related to the shift parameter $\mu_k^{(i)}$ in the dimension *i* of component *k* with length N_i, than $\mathbf{a}(\boldsymbol{\mu}_k)=\mathbf{a}\left(\mu_k^{(R)}\right)\otimes\mathbf{a}\left(\mu_k^{(R-1)}\right)\otimes\ldots\otimes\mathbf{a}\left(\mu_k^{(1)}\right)$ is a vector valued function mapping the real shift parameters from $\mathbb{R}^R$ to a complex vector in $\mathbb{C}^N$ with unit length and size $N=N_1\cdot N_2\cdot\ldots\cdot N_R$. Introducing the four linear projectors $\mathbf{G}_{HH},\mathbf{G}_{HV},\mathbf{G}_{VH},\mathbf{G}_{VV}$, describing the measurement system, we can express the observation of a single specular propagation path of size *M* simply by

$$\mathbf{s}(\boldsymbol{\theta}_k)=\gamma_{HH,k}\cdot\mathbf{G}_{HH}\cdot\mathbf{a}(\boldsymbol{\mu}_k)+\gamma_{HV,k}\cdot\mathbf{G}_{HV}\cdot\mathbf{a}(\boldsymbol{\mu}_k)+\gamma_{VH,k}\cdot\mathbf{G}_{VH}\cdot\mathbf{a}(\boldsymbol{\mu}_k)++\gamma_{VV,k}\cdot\mathbf{G}_{VV}\cdot\mathbf{a}(\boldsymbol{\mu}_k)$$

with the parameter vector

$$\boldsymbol{\theta}_k=\left[\boldsymbol{\mu}_k^T\;\Re\{\gamma_{HH,k}\}\;\Im\{\gamma_{HH,k}\}\;\Re\{\gamma_{HV,k}\}\;\Im\{\gamma_{HV,k}\}\;\Re\{\gamma_{VH,k}\}\;\Im\{\gamma_{VH,k}\}\;\Re\{\gamma_{VV,k}\}\;\Im\{\gamma_{VV,k}\}\right].$$

Let us clarify the meaning of the system matrices $\mathbf{G}_{HH},\mathbf{G}_{HV},\mathbf{G}_{VH},\mathbf{G}_{VV}$ a little bit using an example. We assume the narrowband radio channel has been measured M_t times equally spaced over time using two-dimensional antenna arrays at both the Tx- and the Rx-site with M_T and M_R antenna elements respectively. The radio channel is measured in the frequency domain with a broadband-signal of M_f equally spaced lines around the carrier frequency f_c. Furthermore we assign the normalized shift parameters to the physical parameters in the following fashion ($\mu^{(1)}=f(\alpha),\mu^{(2)}=f(\tau),\mu^{(3)}=f(\varphi_T),\mu^{(4)}=f(\vartheta_T)$, $\mu^{(5)}=f(\varphi_R)$, $\mu^{(6)}=f(\vartheta_R)$). To keep things simple, we will assume narrowband measurements in that sense, that it is sufficient in terms of the measurement accuracy to describe the directional characteristics of the antenna arrays at the carrier frequency, and that the Nyquist sampling theorem is strictly adhered to in all six dimensions. Now using the fact that the far-field beam-pattern of an antenna-array is the two-dimensional Fourier-transform of its effective aperture distribution function EADF [18], we can express the relation between the signals of the antenna array ports and the element beam-patterns using the respective effective aperture distribution functions. Collecting the aperture fields of the Tx- and Rx-array row-wise in the matrices G_{T_H},G_{T_V} and G_{R_H},G_{R_V} respectively, we can use

$$\mathbf{b}_{T_H}\left(\mu^{(3)},\mu^{(4)}\right)=\mathbf{G}_{T_H}\cdot\left(\mathbf{a}\left(\mu^{(4)}\right)\otimes\mathbf{a}\left(\mu^{(3)}\right)\right),\ \mathbf{b}_{T_V}\left(\mu^{(3)},\mu^{(4)}\right)=\mathbf{G}_{T_V}\cdot\left(\mathbf{a}\left(\mu^{(4)}\right)\otimes\mathbf{a}\left(\mu^{(3)}\right)\right),$$

$$\mathbf{b}_{R_H}\left(\mu^{(5)},\mu^{(6)}\right)=\mathbf{G}_{R_H}\cdot\left(\mathbf{a}\left(\mu^{(6)}\right)\otimes\mathbf{a}\left(\mu^{(5)}\right)\right),\text{ and }\mathbf{b}_{R_V}\left(\mu^{(5)},\mu^{(6)}\right)=\mathbf{G}_{R_V}\cdot\left(\mathbf{a}\left(\mu^{(6)}\right)\otimes\mathbf{a}\left(\mu^{(5)}\right)\right)$$

to express the relation between the signals on the antenna array ports and a far-field point source or drain in a fixed distance. Furthermore we use the diagonal matrix $\mathbf{G}_f$ to describe the frequency response of the measurement system and the identity matrix $\mathbf{G}_t=\mathbf{I}$ to describe the time sampling of the MIMO impulse responses. Altogether the matrices

$$\mathbf{G}_{HH}=\mathbf{G}_{R_H}\otimes\mathbf{G}_{T_H}\otimes\mathbf{G}_f\otimes\mathbf{G}_t,\ \mathbf{G}_{HV}=\mathbf{G}_{R_V}\otimes\mathbf{G}_{T_H}\otimes\mathbf{G}_f\otimes\mathbf{G}_t,$$

$$\mathbf{G}_{VH}=\mathbf{G}_{R_H}\otimes\mathbf{G}_{T_V}\otimes\mathbf{G}_f\otimes\mathbf{G}_t,\text{ and }\mathbf{G}_{VV}=\mathbf{G}_{R_V}\otimes\mathbf{G}_{T_V}\otimes\mathbf{G}_f\otimes\mathbf{G}_t$$

describe the measurement system of our example.

In [19] we have shown, that the observed radio channel consists not only of specular components but also of distributed diffuse scatterer (DDS). So taking into account that the radio channel is a linear system, we can say that the observation $\mathbf{s}(\boldsymbol{\theta})$ is up to certain accuracy a superposition of a finite number *K* of specular propagation paths and a complex vector $\mathbf{n}$ drawn from a multivariate circular Gaussian process describing the distribution of the observed distributed diffuse scatterer and the measurement noise. For a discussion about the structure of the covariance matrix $\mathbf{R}(\boldsymbol{\theta}_{dds})$ of this Gaussian process see [19].

III. Maximum Likelihood Estimation

Introducing the complete parameter vector containing the parameters of all K components

$$\boldsymbol{\theta}_{sp} = \left[\boldsymbol{\mu}^T \quad \Re\{\boldsymbol{\gamma}_{HH}^T\} \quad \Im\{\boldsymbol{\gamma}_{HH}^T\} \quad \Re\{\boldsymbol{\gamma}_{HV}^T\} \quad \Im\{\boldsymbol{\gamma}_{HV}^T\} \quad \Re\{\boldsymbol{\gamma}_{VH}^T\} \quad \Im\{\boldsymbol{\gamma}_{VV}^T\} \quad \Re\{\boldsymbol{\gamma}_{VV}^T\} \quad \Im\{\gamma_{VV,k}\}\right]^T$$

our observation can be expressed as

$$\mathbf{x} = \mathbf{n} + \sum_{k=1}^{K} \mathbf{s}(\boldsymbol{\theta}_k) = \mathbf{n} + \mathbf{s}(\boldsymbol{\theta}_{sp}).$$

The probability density function of the observation $\mathbf{x}$ is

$$pdf(\mathbf{x}|\boldsymbol{\theta}_{sp}, \boldsymbol{\theta}_{dds}) = \frac{1}{\boldsymbol{\pi}^M \det(\mathbf{R}(\boldsymbol{\theta}_{dds}))} \mathrm{e}^{-(\mathbf{x}-\mathbf{s}(\boldsymbol{\theta}_{sp}))^H \mathbf{R}(\boldsymbol{\theta}_{dds})^{-1} \cdot (\mathbf{x}-\mathbf{s}(\boldsymbol{\theta}_{sp}))}$$

and the related log-likelihood function is

$$L(\mathbf{x}; \boldsymbol{\theta}_{sp}, \boldsymbol{\theta}_{dds}) = -M \cdot \ln(\pi) - \ln(\det(\mathbf{R}(\boldsymbol{\theta}_{dds}))) - (\mathbf{x} - \mathbf{s}(\boldsymbol{\theta}_{sp}))^H \cdot \mathbf{R}(\boldsymbol{\theta}_{dds})^{-1} \cdot (\mathbf{x} - \mathbf{s}(\boldsymbol{\theta}_{sp})).$$

Using the column-wise Kronecker or Khatri-Rao product $\Diamond$ the complete data-model for the specular paths can be expressed in the following way

$$\begin{aligned} \mathbf{s}(\boldsymbol{\theta}_{sp}) = {} & \mathbf{B}_{R_H} \Diamond \mathbf{B}_{T_H} \Diamond \mathbf{B}_f \Diamond \mathbf{B}_t \cdot \boldsymbol{\gamma}_{HH} + \\ & \mathbf{B}_{R_V} \Diamond \mathbf{B}_{T_H} \Diamond \mathbf{B}_f \Diamond \mathbf{B}_t \cdot \boldsymbol{\gamma}_{HV} + \\ & \mathbf{B}_{R_H} \Diamond \mathbf{B}_{T_V} \Diamond \mathbf{B}_f \Diamond \mathbf{B}_t \cdot \boldsymbol{\gamma}_{VH} + \\ & \mathbf{B}_{R_V} \Diamond \mathbf{B}_{T_V} \Diamond \mathbf{B}_f \Diamond \mathbf{B}_t \cdot \boldsymbol{\gamma}_{VV} \end{aligned}$$

with

$$\mathbf{B}_{R_H} = \mathbf{G}_{R_H} \cdot \left[\mathbf{a}(\mu_1^{(6)}) \otimes \mathbf{a}(\mu_1^{(5)}) \quad \ldots \quad \mathbf{a}(\mu_K^{(6)}) \otimes \mathbf{a}(\mu_K^{(5)})\right],$$

$$\mathbf{B}_{R_V} = \mathbf{G}_{R_V} \cdot \left[\mathbf{a}(\mu_1^{(6)}) \otimes \mathbf{a}(\mu_1^{(5)}) \quad \ldots \quad \mathbf{a}(\mu_K^{(6)}) \otimes \mathbf{a}(\mu_K^{(5)})\right],$$

$$\mathbf{B}_{T_H} = \mathbf{G}_{T_H} \cdot \left[\mathbf{a}(\mu_1^{(4)}) \otimes \mathbf{a}(\mu_1^{(3)}) \quad \ldots \quad \mathbf{a}(\mu_K^{(4)}) \otimes \mathbf{a}(\mu_K^{(3)})\right],$$

$$\mathbf{B}_{T_V} = \mathbf{G}_{T_V} \cdot \left[\mathbf{a}(\mu_1^{(4)}) \otimes \mathbf{a}(\mu_1^{(3)}) \quad \ldots \quad \mathbf{a}(\mu_K^{(4)}) \otimes \mathbf{a}(\mu_K^{(3)})\right],$$

$$\mathbf{B}_f = \mathbf{G}_f \cdot \left[\mathbf{a}(\mu_1^{(2)}) \quad \ldots \quad \mathbf{a}(\mu_K^{(2)})\right], \text{ and}$$

$$\mathbf{B}_t = \mathbf{G}_t \cdot \left[\mathbf{a}(\mu_1^{(1)}) \quad \ldots \quad \mathbf{a}(\mu_K^{(1)})\right].$$

Where we have, for notational convenience, dropped the dependency of the matrices $\mathbf{B}$ from the parameters $\boldsymbol{\mu}$.

Since the parameter vectors $\boldsymbol{\theta}_{sp}$, and $\boldsymbol{\theta}_{dds}$ are independent parameter sets, we use the space alternating generalized expectation maximization algorithm (SAGE) [8] and maximize the log-likelihood function in an alternating manner. We alternate between the maximization of the log-likelihood function regarding the parameters of the distributed diffuse scatterer $\boldsymbol{\theta}_{dds}$ and the parameters of the specular components $\boldsymbol{\theta}_{sp}$. For the optimization of the parameters $\boldsymbol{\theta}_{dds}$ we apply the algorithm described in [19]. The optimization of the parameters $\boldsymbol{\theta}_{sp}$ is carried out by our conjugate gradient based algorithm described in [17]. The algorithm is based on the observation that the minimization step

$$\hat{\boldsymbol{\theta}}_{sp} = \arg\min_{\boldsymbol{\theta}_{sp}} (\mathbf{x} - \mathbf{s}(\boldsymbol{\theta}_{sp}))^H \cdot \mathbf{R}(\hat{\boldsymbol{\theta}}_{dds})^{-1} \cdot (\mathbf{x} - \mathbf{s}(\boldsymbol{\theta}_{sp}))$$

is essentially a nonlinear weighted least squares problem NLWLS. Since the data model can be expressed algebraically, the calculation of the Jacobian and the Hessian is simple. One advantage of the conjugate gradient methods Gauss-Newton or better Levenberg-Marquardt is, that the approximation of the Hessian used is also an estimate of the Fisher information matrix. Since the inverse of the Fisher information matrix gives the Cramér-Rao bound of the model parameters, the inverse of the Hessian provides an estimate of the variance of the parameters estimated [17].

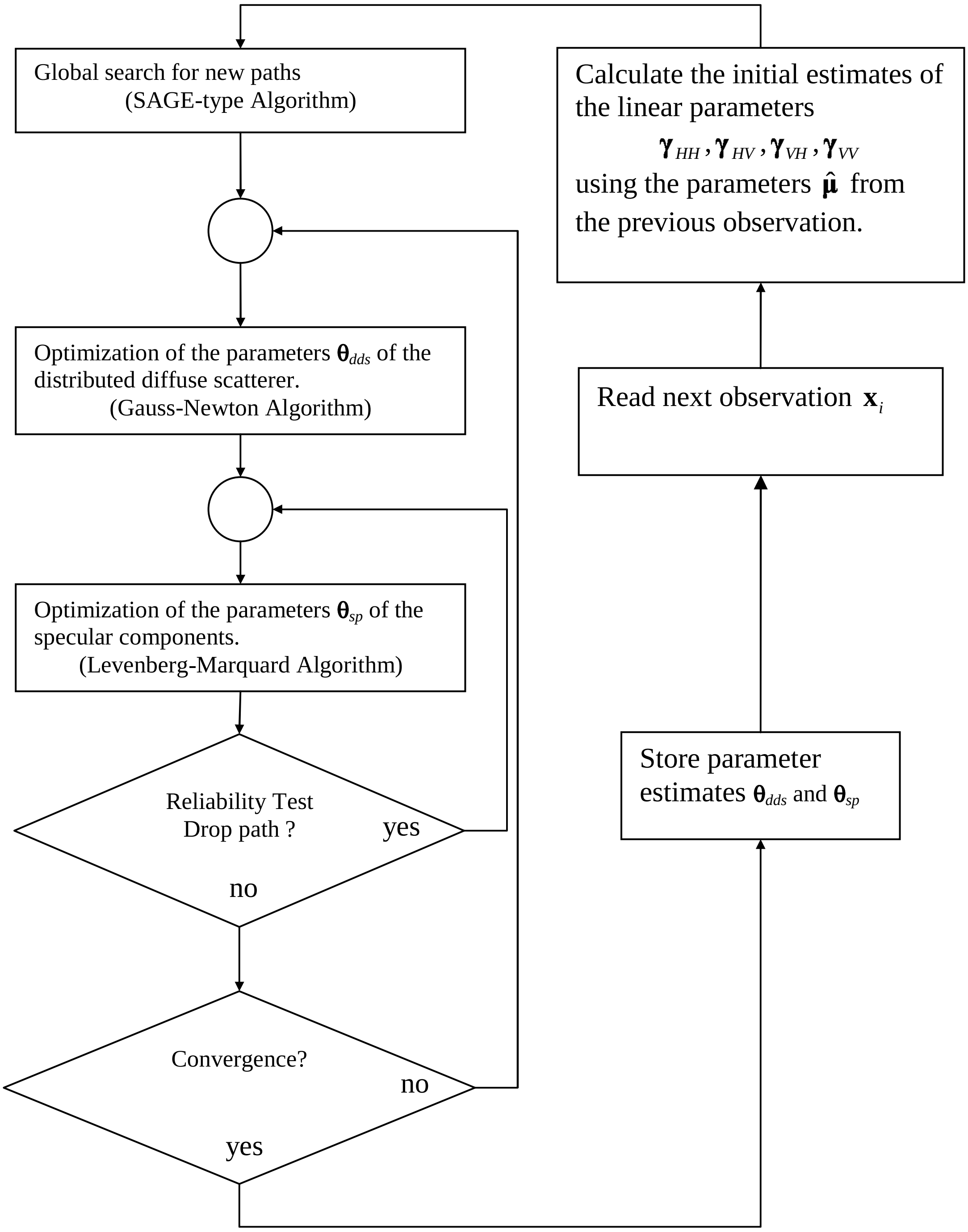

Figure 1: RIMAX parameter estimation algorithm outline

The estimated variance of the estimated parameters can be used to estimate the relative variance of the parameter estimates. If the parameters of a propagation path are unreliable the RIMAX algorithm drops the path.

For the initialization of the parameters the RIMAX-algorithm uses at first the estimated angles, delays and Doppler-shifts of the previous observation and estimates the linear parameters (path weights) for the actual observation. In a second initialization step a coordinate (parameter) -wise search algorithm (SAGE-type) is applied to search for raw parameter estimates of new propagation paths in the scenario. The basic blocks of the RIMAX-algorithm are shown in Figure 1.

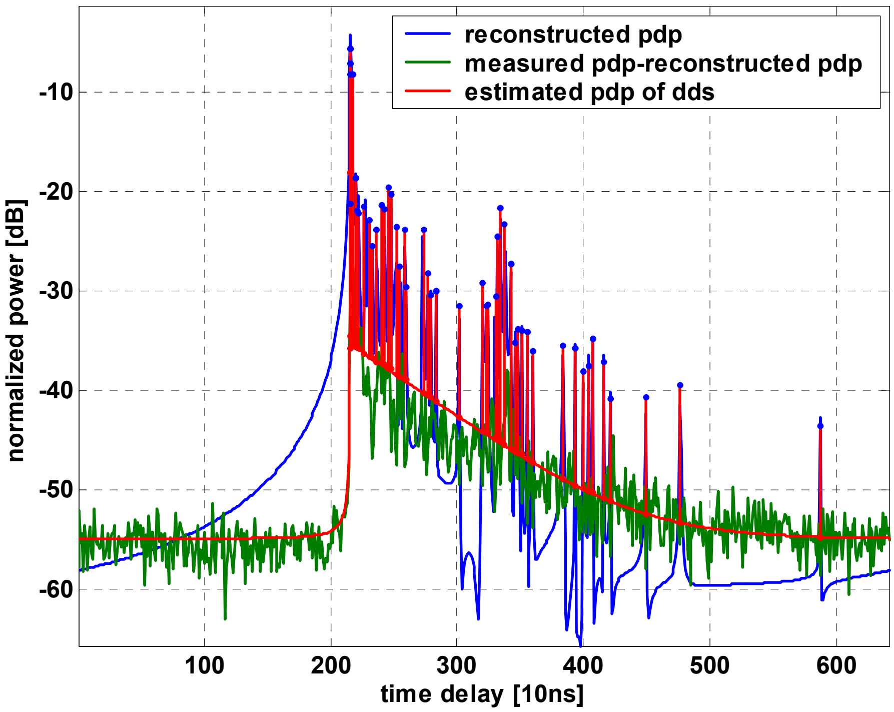

Figure 2: Example for the reconstructed power delay profile of the specular paths (blue) and the estimated power delay profile of the distributed diffuse scatterers plus noise (red).

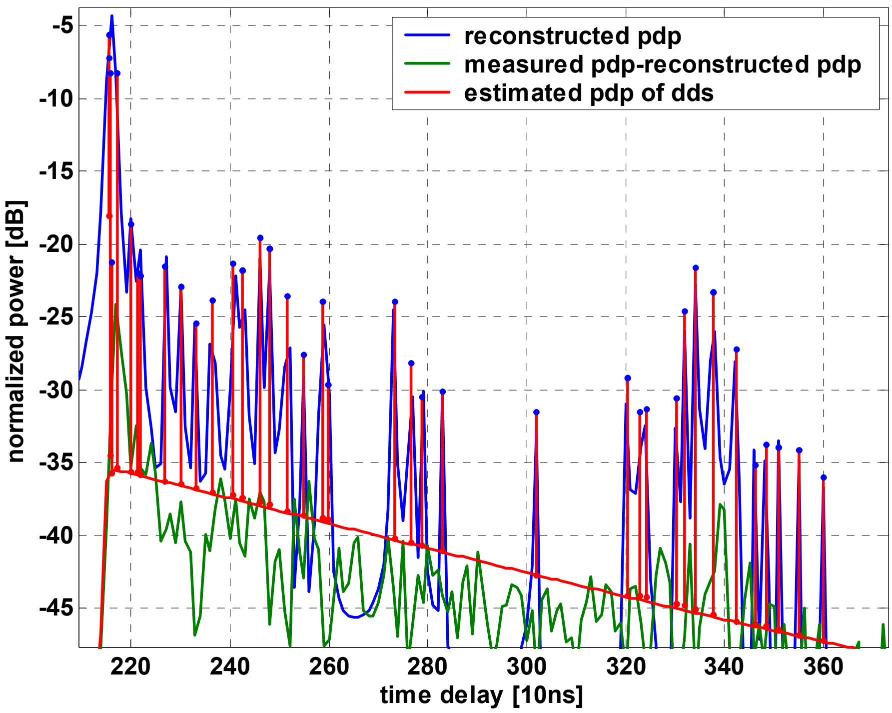

Figure 3: Closer view of Figure 2, the blue dots show the power of the estimated path weights the red dots their estimated variance.

IV. Parameter Estimation Results

In Figure 2-7 some results for parameters estimated using the RIMAX algorithm are shown. The measurements have been carried out in a street micro-cell scenario. The position of the transmitter and the receiver was fixed. The parameter variations are caused by the movement of reflectors and scatterers (mainly cars). The total measurement time was approx. 135 seconds.

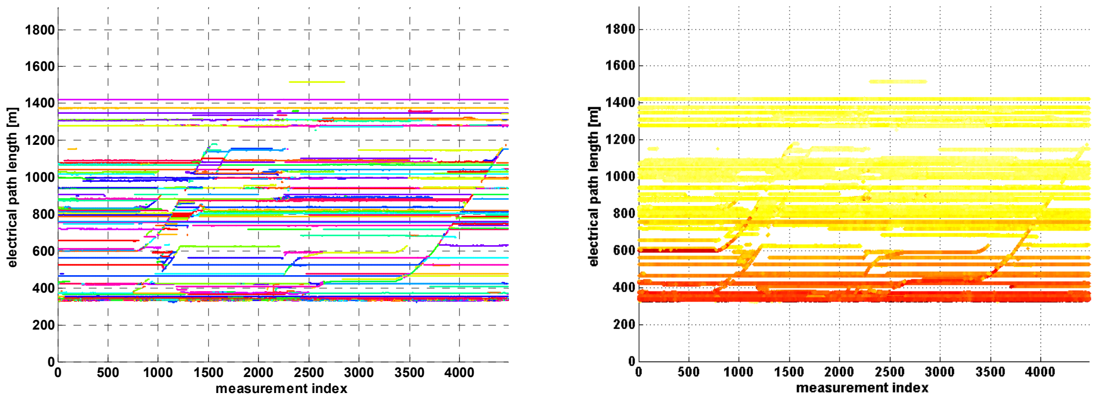

Figure 4: living time (segment length) of the estimated propagation paths (left), estimated length of the propagation paths (right) (stronger paths have darker colors)

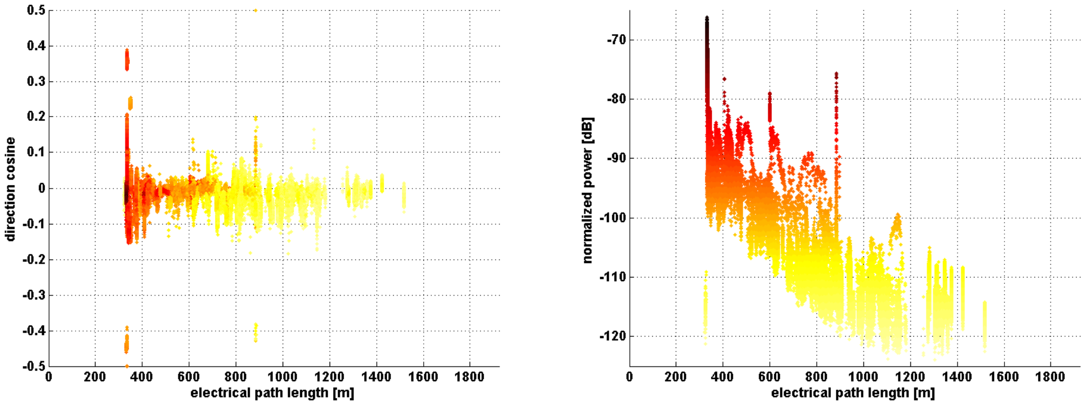

Figure 5: estimated azimuth angles (left) at the BS, and estimated path weights (right) of all estimated paths

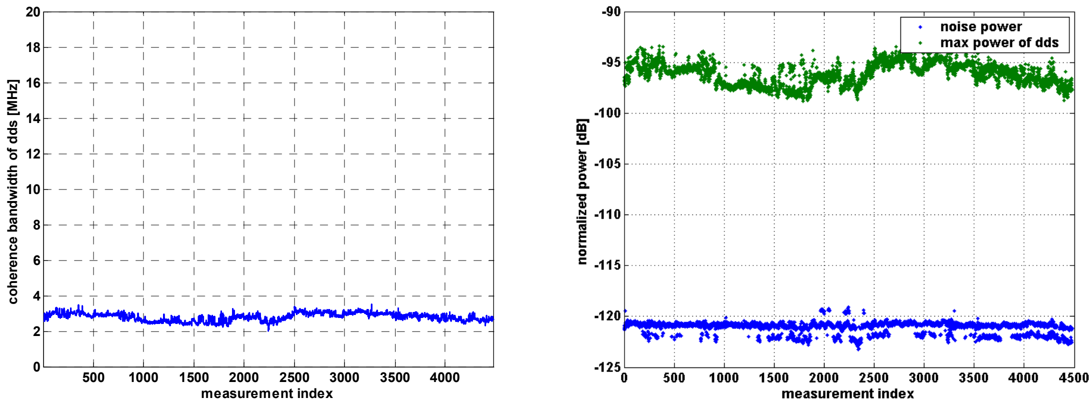

Figure 6: estimated coherence bandwidth of the observed distributed diffuse scatterers (left), estimated maximum power of the distributed diffuse scatterer and estimated measurement noise power (right)

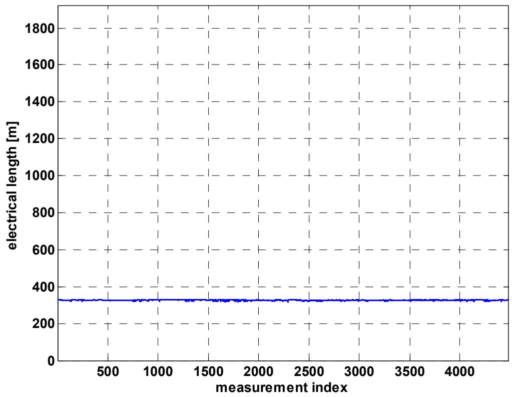

Figure 7: estimated base delay of the distributed diffuse scatterer

Conclusion

We have introduced a multidimensional maximum likelihood parameter estimator for the estimation of radio channel parameters from channel sounding measurements. The algorithm estimates jointly the parameters of the specular components (propagation paths) as well as the parameters of the distributed diffuse scatterer.

The algorithm is based on the conjugate gradient optimization strategy. It has a low complexity as e.g. the SAGE-algorithm, if the number of paths (components) is small compared to the number of observations, what is typical for multidimensional radio channel sounding measurements. The algorithm provides additionally an estimate of the variance of the calculated parameters, yielding reliability information of the channel parameters estimated.

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