A Novel Environment Characterisation Metric for Clustered MIMO Channels Used to Validate a SAGE Parameter Estimator

Nicolai Czink[1], Giovanni Del Galdo[2], Xuefeng Yin[3], Christoph Mecklenbräuker[1]

[1]Forschungszentrum Telekommunikation Wien (ftw.), Vienna, Austria
[2]Ilmenau University of Technology, Communications Research Laboratory, Ilmenau, Germany
[3]Department of Communication Technology, Aalborg University, Aalborg, Denmark
E-Mail: czink@ftw.at

***Abstract*— In this work we introduce a novel metric for characterizing the double-directional propagation environment and use this metric to assess the performance of a SAGE parameter estimator for MIMO channels.**

Using the IlmProp, a geometry-based MIMO channel model, we construct synthetic channels for three different scenarios showing: (i) well separated, dense clustered propagation paths with single-bounce scattering, (ii) clustered propagation paths which are spread wider, (iii) no clusters and double-bounce-only reflections. We model the scatterers and the Rx in the environment as fixed, but the Tx as moving.

The Initialization and Search-Improved SAGE estimation tool is used to extract the propagation paths from the constructed channels. Both true and estimated paths are fed to the new system-independent metric which genuinely reflects the structure of the channel and the compactness of propagation paths. We use this metric to decide on the accuracy of the channel estimator.

The results show a convincing conformance between true and estimated paths.

I. Introduction

Novel MIMO channel models use the concept of clustered propagation paths (e.g. [1]), where these clusters need to be parametrized from measurements. Lately, automatic cluster-finding algorithms have emerged, but they are basedon the precondition that the environment is clustered. Yet, no metric has been developed to judge how clustered a propagation environment is. Previously, a metric to quantify the compactness of the direction of paths was introduced in [2], [3], but this metric focuses on distinct ends of the link, only. We extend this concept to the whole double-directional parameter domain, which enables us to judge the compactness of a propagation scenario. The novel *environment characterization metric* (ECM) is system-independent and allows to characterise the environment in a compact way.

To parametrize cluster-based models, channel parameter estimators are used to extract propagation paths from MIMO measurements, then cluster finding and tracking algorithms try to get hold of cluster parameters. The high-resolution parameter estimators are essential for characterizing the double-directional radio channel, since they allow for estimating individual propagation paths beyond the intrinsic resolution of the measurement system.

These parameter estimators were shown to be well-suited for estimating distinct propagation paths [4], but no analysis was done for clustered paths. Another study describes the impact of a low-resolution parameter estimator [5]. Already estimated paths from MIMO measurements are used as input data for generating channel matrices. Subsequently a parameter estimator re-estimates the data. Note that the effects of the initial parameter estimator are already present in the input data, hence this scheme cannot truly judge the true performance of the estimator.

To assess the accuracy of the parameter estimator, which is based on the Initialization and Search-Improved SAGE (ISIS) algorithm [4], we apply it to smoothly time-variant synthetic channels for three different kinds of propagation environments to cover different grades of clustering. Synthetic channels are advantageous as the exact location of the propagation paths is known. For generating the channel realizations the IlmProp MIMO channel model is used.

The comparison between true and estimated paths is quite tricky, as the parameter estimator typically does not estimate the correct number of paths. Furthermore, the data model might not necessarily fit. Still, the estimation results may describe the propagation environment sufficiently well. To assess the accuracy of the channel estimation, the used metric should reflect the multi-path structure of the true and the estimated channel. For this reason we propose to use the ECM.

This paper is organised as follows: the novel environment characterization metric is detailed in Section II. Section III describes the framework for the test of the channel estimator. The synthetic environments are presented in Section IV. A short description of the SAGE estimator used is given in Section V. Finally we present the results in Section VI. With Section VII we conclude.

II. Environment characterisation metric

A novel quantification metric for directional spreads was introduced in [2], [3]. This metric can be seen as a worthwhile extension of the angular spread metric. However, it focuses only on one side of the link, either Tx or Rx. We extend this idea to characterise the environment with a single global

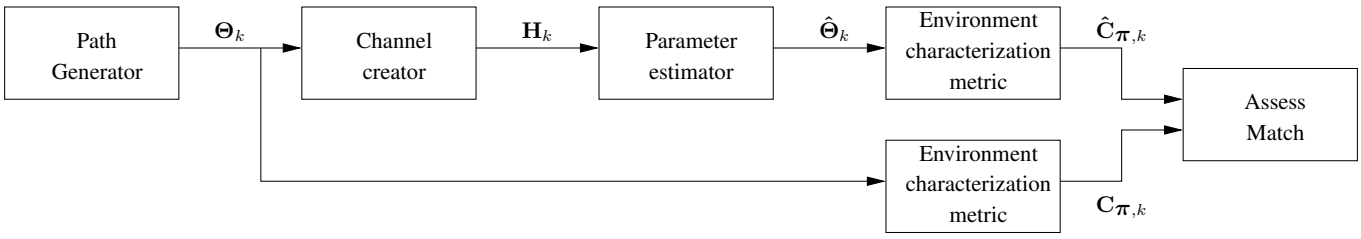


Fig. 1. Framework for assessing estimator performance

metric. We achieve this by considering the double-directional and delay domain [6], where paths are characterized by directions of departure, directions of arrival, delays and path weights.

We assume that the environment can be sufficiently described by K subsequent snapshots in time, where each snapshot is described by L_k propagation paths between Tx and Rx. The l-th path in the k-th snapshot is described by the path parameter vector $\boldsymbol{\theta}_{kl}$, containing its complex-valued path-weight (γ_{kl}), delay (τ_{kl}), azimuth and elevation of departure ($\varphi_{\text{Tx},kl}$ and $\phi_{\text{Tx},kl}$), and azimuth and elevation of arrival ($\varphi_{\text{Rx},kl}$ and $\phi_{\text{Rx},kl}$), hence

$$\boldsymbol{\theta}_{kl} = [\gamma_{kl}\ \tau_{kl}\ \varphi_{\text{Tx},kl}\ \phi_{\text{Tx},kl}\ \varphi_{\text{Rx},kl}\ \phi_{\text{Rx},kl}]^{\text{T}}, \quad (1)$$

$$l = 1 \dots L_k, \quad k = 1 \dots K. \quad (2)$$

All paths in one snapshot are collected in

$$\mathbf{\Theta}_k = [\boldsymbol{\theta}_{k1} \dots \boldsymbol{\theta}_{kL_k}],\ k = 1 \dots K. \quad (3)$$

Using a specific system model with system parameters and antenna patterns, frequency-dependent channel matrices can be calculated for each snapshot in time.

The new metric is calculated for every single snapshot k, so we will skip this index for better readability. As the metric has to cope with data in different units (angular and delay), it is essential to transform the parameter matrix by proper scaling of its elements. For every path l, angular data is transformed into coordinates on the unit sphere for both, Rx and Tx. For angles of arrival the transformation is given as

$$\begin{bmatrix} x_{\text{Rx},l} \\ y_{\text{Rx},l} \\ z_{\text{Rx},l} \end{bmatrix} = \frac{1}{2} \begin{bmatrix} \sin\phi_{\text{Rx},l} \cdot \sin\varphi_{\text{Rx},l} \\ \sin\phi_{\text{Rx},l} \cdot \cos\varphi_{\text{Rx},l} \\ \cos\phi_{\text{Rx},l} \end{bmatrix}, \quad (4)$$

for angles at the Tx it reads similarly. The scaling is done such that the maximum Euclidean distance between two paths is limited to 1.

Delay is scaled by the maximum delay that occurs in the considered snapshot [7], hence

$$\tilde{\tau}_l = \frac{\tau_l}{\max_l \tau_l} \quad (5)$$

Every path is now described by seven (dimensionless) parameters collected in

$$\boldsymbol{\pi}_l = [x_{\text{Rx},l}\ y_{\text{Rx},l}\ z_{\text{Rx},l}\ x_{\text{Tx},l}\ y_{\text{Tx},l}\ z_{\text{Tx},l}\ \tilde{\tau}_l]^{\text{T}} \quad (6)$$

and its power $|\gamma_l|^2$. When considering propagation in the azimuthal plane only, the z-direction must be excluded.

The mean parameter vector is then given as

$$\bar{\boldsymbol{\pi}} = \frac{\sum_{l=1}^{L} |\gamma_l|^2 \boldsymbol{\pi}_l}{\sum_{l=1}^{L} |\gamma_l|^2}. \quad (7)$$

We propose to use the sample covariance of the path parameter vector as novel environment characterisation metric (ECM)

$$\mathbf{C}_{\boldsymbol{\pi}} = \frac{\sum_{l=1}^{L} |\gamma_l|^2 (\boldsymbol{\pi}_l - \bar{\boldsymbol{\pi}})(\boldsymbol{\pi}_l - \bar{\boldsymbol{\pi}})^T}{\sum_{l=1}^{L} |\gamma_l|^2}. \quad (8)$$

This metric shows following properties:

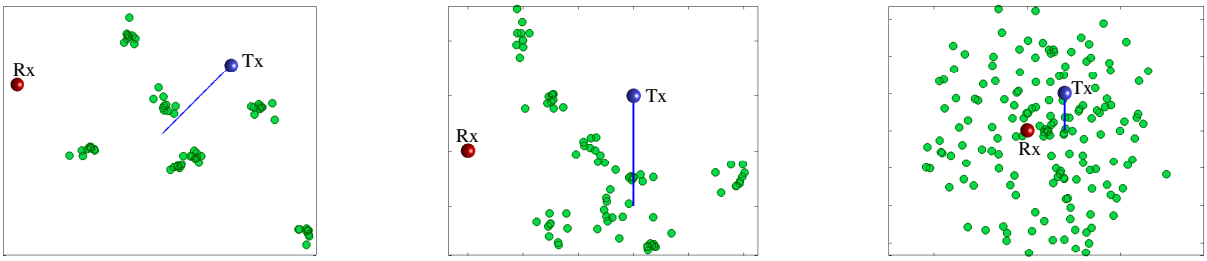
- The metric is *system independent* as it is calculated from the propagation paths directly.
- The main diagonal contains the directional spreads of the single components at Rx and Tx and the (normalized) delay spread.
- The singular values (SV) of $\mathbf{C}_{\boldsymbol{\pi}}$ can be interpreted as "fingerprint" of the scenario, furthermore one can judge the compactness of the paths in the channel, which will be shown in the results.
- The trace $\text{tr}\{\mathbf{C}_{\boldsymbol{\pi}}\}$ is the sum of the directional spreads [8] at Rx and Tx plus the (normalized) delay spread. Note that the trace is dominated by the *large SVs*.
- The determinant $\det\{\mathbf{C}_{\boldsymbol{\pi}}\}$ has similar importance like detailed in [2], [3]. Note that the determinant is dominated by the *small SVs*.

In the Results (see Section VI) we will show the implication of the SVs and how to use them for judging the estimator performance.

III. Validation framework

Validating high-resolution estimation algorithms is difficult for several reasons. First, the data model assumed by the estimator does not necessarily fit the true propagation mechanisms (*model mismatch*). Furthermore, even assuming that the data model were exact, the algorithm could still suffer from a *model order mismatch*, i.e., estimating the wrong number of propagation paths.

In this work we focus on the latter case, where we assume that the true number of paths is larger than the number of estimated ones. However, the framework introduced in this paper can as well be applied to both kinds of deficiencies.



(a) (b) (c)

Fig. 2. Scenarios used for comparing the estimator performance: (a) few clustered paths, (b) larger clusters, (c) rich scattering

Since the number of estimated paths usually does not match the true number, well-known error metrics like the mean-squared estimation error cannot be applied. Also the "reconstruction error", i.e. the difference between true and (reconstructed) estimated MIMO channel matrix does not reflect properties of the channel well. For this reason we propose to use the ECM, a novel metric to characterize the channel (cf. Section II).

For testing the accuracy of the channel estimator we use the framework shown in Figure 1 for different environments. First, path parameters $\mathbf{\Theta}_k$ (cf. (1) and (3)) are generated using the IlmProp channel model (see Section IV-A). For simplicity we disregard elevations. Using specific system parameters and antenna patterns, frequency-dependent channel matrices are calculated for each snapshot in time.

Afterwards, ISIS is used to estimate the channel parameters (see Section V). The outcome are the estimated parameters for each channel snapshot $\hat{\mathbf{\Theta}}_k$.

The snapshots with the generated paths and with the estimated ones are fed to the ECM, which is system-independent (see Section II). This allows for fair comparison of the true and estimated parameters.

The final outcome is the match between true and estimated parameters.

IV. Simulated Environments

We use the IlmProp Channel model for generating the environments and calculating the frequency-dependent channel matrices [9], [10].

A. IlmProp Channel Model

The IlmProp is a flexible geometry-based Multi-User MIMO channel modelling tool, capable of dealing with time variant frequency selective scenarios. Figure 3 illustrates the capabilities of the IlmProp. Three mobiles (M1, M2, and M3) move around the Base Station (BS). Their curvilinear trajectories are shown. The BS (Rx) and mobile terminals (Tx) can employ any number of antennas arranged in an array with an arbitrary geometry. The channel is computed as a sum of the Line Of Sight (LOS) and of a number of rays which represent the multi-path components. The latter are obtained by point-like scatterers, which can be placed at will. The model

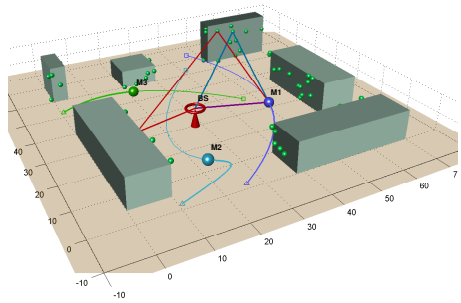
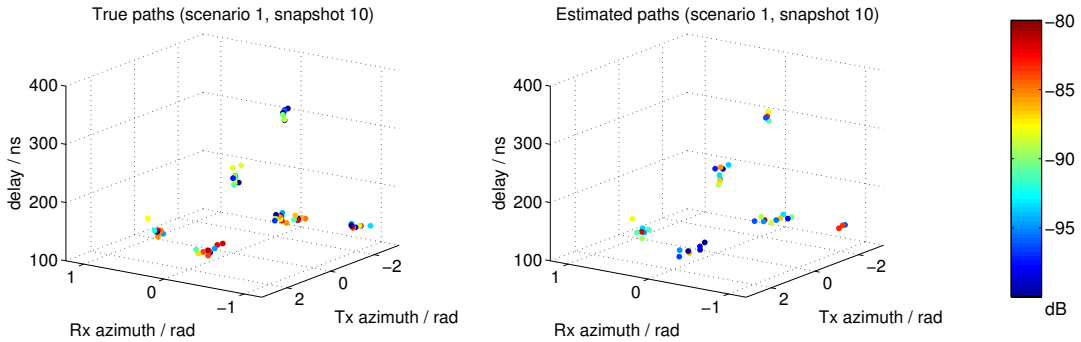


Fig. 3. Sample scenario generated with IlmProp to illustrate the capabilities of the channel model

supports both single- and multiple-reflections. Obstacles (such as buildings), which can obstruct the propagation paths can also be included. In Figure 3 the LOS for M1, a single bounce ray and a double bounce ray are shown. The information about the location of the scatterers, and how the paths are linked to them can be set arbitrarily. These informations can can be also be derived via parameter estimations from channel measurements. The information about the scenario is stored in form of Cartesian coordinates and their evolution in time. More information on the model, as well as the source code and some exemplary scenarios can be found at *http://tu-ilmenau.de/ilmprop*.

B. Modelled Scenarios

We decide to compare the accuracy of channel estimation for three different types of scenarios showing (i) well separated, dense clustered propagation paths with single-bounce scattering, (ii) clustered propagation paths which are spread wider, (iii) no clusters and double-bounce-only reflections. The scenarios are shown in Figure 2, where the red ball denotes the position of the Rx array, the blue ball denotes the Tx array at its final point, the blue line shows the Tx route, and the green circles indicate scatterers. The channels were generated for a bandwidth of 100 MHz, with 510 frequency samples. The Tx employs a Uniform Linear Array with 15 sensors 0.45λ spaced and slightly directive beam patterns. The Rx employs a Uniform Circular Array with 15 sensors 0.4λ spaced and slightly directive beam patterns. Only vertical-to-



(a) (b)

Fig. 4. Visual comparison of true and estimated parameters.

vertical polarization is considered. No noise was added in all three scenarios.

For the clustered scenarios (a) and (b), only single-bounce scattering was assumed, whereas for the rich-scattering scenario (c) only double scattering paths occurs, where always two scatterers were picked out randomly of the scenario to form one double-scattering path. The latter scenario is quite unrealistic, but serves well as worst-case example for rich-scattering.

V. Channel Estimator

The ISIS algorithm [4] was applied to the synthetic data generated by IlmProp under different scenarios. Comparing with the original SAGE algorithm [11], the ISIS algorithm exhibits a performance improvement in terms of convergence speed, detection ability of the weak paths and computational effort [12]. The parameters to be estimated out of the channel impulse responses are azimuths of arrival, azimuths of departure, propagation delays and polarization matrices of 40 paths in individual snapshots.

The selected quantization steps for the M-step of the algorithm are respectively 0.5ns in delay and $0.1°$ in azimuth. The dynamic range for the absolute path weights equals 25dB. Twenty iteration cycles are performed to extract the estimates described above.

VI. Results

To give a first impression of the accuracy of the parameter estimator, Figure 4 shows the true and estimated paths in the parameter domain for one time snapshot of the first scenario. One can observe that the estimator seems to be well able to capture the properties of the environment, even if the number of estimated paths is lower than the true number of paths. Note that the estimated path powers as well as the estimated locations of the paths do not coincide with the real paths in general, but the estimator rather resolves the clusters of paths quite accurately.

Hence, we choose to evaluate the estimator by using the ECM. For each scenario we calculated the ECM for the k-th snapshots for the true and estimated paths denoted by $\mathbf{C}_{\boldsymbol{\pi},k}$ and $\hat{\mathbf{C}}_{\boldsymbol{\pi},k}$, and the respective singular values (SV) σ_{kd}^2 and $\hat{\sigma}_{kd}^2$, where $d = 1 \dots D$ and D denotes the dimension of $\mathbf{C}_{\boldsymbol{\pi},k}$.

Figure 5 shows these SVs in dB for the three different scenarios. The values for the true paths are indicated by black lines, the estimated paths by red lines and the different SVs by different marker types.

To discuss the significance of the new metric, we first focus only on the true paths results. In Figure 5(a) one can observe a large distance between the second and third SV, and between the 4th and 5th SV, where especially the last value of Scenario 1 changes strongly over time. Figure 5(b) show also a large distance between the SVs. In Figure 5(c) the SVs are very close to each other and do not change significantly. This gives rise to the following conjecture:

> *The distances between the SVs of the environment characterisation matrix $\mathbf{C}_{\boldsymbol{\pi}}$ provide information about the compactness of the paths in the environment.*

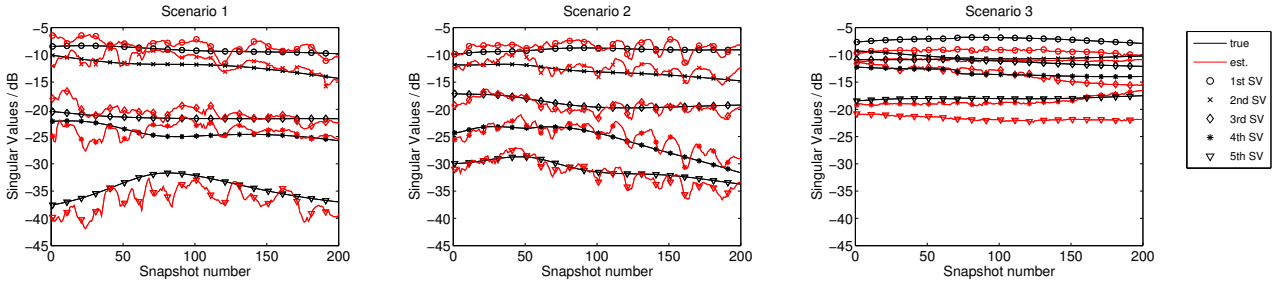
To assess the performance of the parameter estimator, we compare the SVs of the ECM gained from the estimated paths (red/lighter lines) with the ones gained from the true paths (see Figure 5).

For the first two environments with clustered propagation paths, one can observe that the general trend is the same, but the curves seem to vary around the correct value. The reason for this is the destructive/constructive interference of different paths at the Rx, which attenuates some clusters and amplifies others.

In the third (rich scattering) environment the SVs are typically underestimated, which indicates that the true propagation paths are spread wider than the estimated paths. In this instance, the parameter estimator suffers from the model order mismatch, a larger number of paths would be necessary to reflect the scenario correctly.

To quantify the deviation of the estimator we propose to use the mean deviation of all SVs over all snapshots from the true value, hence

$$\mathcal{E} = \frac{1}{ND} \sum_{k=1}^{K} \sum_{d=1}^{D} |\sigma_{kd,[\mathrm{dB}]}^2 - \hat{\sigma}_{kd,[\mathrm{dB}]}^2|, \tag{9}$$



(a) (b) (c)

Fig. 5. Singular values of the environment characterisation metric $\mathbf{C}_{\boldsymbol{\pi}}$ for the true and estimated parameters from the three scenarios.

TABLE I

MEAN DEVIATION OF THE PARAMETER ESTIMATOR

Scenario	Deviation $\mathcal{E}$
Scenario 1	1.41 dB
Scenario 2	0.99 dB
Scenario 3	2.78 dB

where $\sigma^2_{kd,[\mathrm{dB}]}$ and $\hat{\sigma}^2_{kd,[\mathrm{dB}]}$ denotes the value of the respective SV in dB.

The mean errors for the three considered scenarios are given in Table I. Interestingly, the values for the first two scenarios are quite similar, but the deviation is larger for the rich-scattering environment.

VII. CONCLUSIONS

We presented the *environment characterization metric* (ECM), a novel metric for characterizing the double-directional propagation environment, which we use to assess the performance of a high-resolution parameter estimator.

The ECM is calculated from the propagation paths directly, hence it is *system independent*. It reflects the compactness of the paths and thereby gives a "fingerprint" of the environment.

When comparing the fingerprints for true and estimated scenarios, we derived a criterion for the goodness of a parameter estimator. To demonstrate the significance of the ECM, we assess the quality of the ISIS (initialization and search improved-SAGE) parameter estimator. We use the estimator on synthetic channels from different scenarios generated by the IlmProp channel model and compare the results using the metric.

Simulations show that the ECM is well able to characterize the environments. Furthermore, we found that the ISIS algorithm is suitable for reflecting the true environment, with better performance for clustered scenarios.

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REFERENCES

[1] L. Correia, Ed., *Mobile Broadband Multimedia Networks*. To be published by Elsevier, 2006.

[2] A. Pal, M. Beach, and A. Nix, "A quantification of 3-d directional spread from small-scale fading analysis," in *COST 273 Post-Project Meeting*, Lisbon, Portugal, Nov. 2005.

[3] ——, "A quantification of 3-d directional spread from small-scale fading analysis," *accepted for publication at IEEE International Conference on Communications*, June 2006, Istanbul, Turkey.

[4] B. H. Fleury, X. Yin, P. Jourdan, and A. Stucki, "High-resolution channel parameter estimation for communication systems equipped with antenna arrays," *Proc. 13th IFAC Symposium on System Identification (SYSID 2003), Rotterdam, The Netherlands*, no. ISC-379, 2003.

[5] M. Mustonen, P. Suvikunnas, and P. Vainikainen, "Reliability analysis of multidimensional propagation channel characterization," in *WPMC*, Aalborg, Denmark, 2005.

[6] M. Steinbauer, A. Molisch, and E. Bonek, "The double-directional radio channel," *IEEE Antennas and Propagation Magazine*, vol. 43, no. 4, pp. 51 – 63, Aug. 2001.

[7] M. Steinbauer, H. Özcelik, H. Hofstetter, C. Mecklenbräuker, and E. Bonek, "How to quantify multipath separation," *IEICE Trans. Electron.*, vol. E85, no. 3, pp. 552–557, March 2002.

[8] B. H. Fleury, "First- and second-order characterization of direction dispersion and space selectivity in the radio channel," *IEEE Transactions on Information Theory*, vol. IT-46, no. 6, pp. 2027–2044, September 2000.

[9] G. Del Galdo, M. Haardt, and C. Schneider, "Geometry-based channel modelling of MIMO channels in comparison with channel sounder measurements," *Advances in Radio Science – Kleinheubacher Berichte*, pp. 117–126, October 2003.

[10] "More information on the model, as well as the source code and some exemplary scenarios can be found at *http://tu-ilmenau.de/ilmprop*."

[11] B. H. Fleury, M. Tschudin, R. Heddergott, D. Dahlhaus, and K. I. Pedersen, "Channel parameter estimation in mobile radio environments using the SAGE algorithm," *IEEE JSAC*, no. 3, pp. 434–450, 17 1999.

[12] B. H. Fleury, X. Yin, K. G. Rohbrandt, P. Jourdan, and A. Stucki, "Performance of a high-resolution scheme for joint estimation of delay and bidirection dispersion in the radio channel," *Proc. IEEE Vehicular Technology Conference, VTC 2002 Spring*, vol. 1, pp. 522–526, may 2002.