PARAMETERIZING GEOMETRY-BASED STOCHASTIC MIMO CHANNEL MODELS FROM MEASUREMENTS USING CORRELATED CLUSTERS

Nicolai Czink[1,2], *Ernst Bonek*[1], *Jukka-Pekka Nuutinen*[3], *Juha Ylitalo*[3,4]

[1]Institut für Nachrichtentechnik und Hochfrequenztechnik, Technische Universität Wien, Austria
[2]Forschungszentrum Telekommunikation Wien (ftw.), Vienna, Austria
[3]Centre for Wireless Communications, University of Oulu, Finland
[4]Elektrobit, Finland

ABSTRACT

Geometry-based stochastic MIMO channel models using the concept of multipath clusters are advantageous to model the spatial structure of the channel accurately and in a intuitive manner. However, they are difficult to parameterize. This becomes evident in current (quasi-)standard models, which provide default parameters to cover the environments of interest, yet the model fit is not always convincing. The parameterization is not accurate enough.

We present an automatic framework to obtain the models' *cluster* parameters, which have significant impact on the model accuracy. After applying the framework to indoor MIMO channel measurements, we discuss the results for following model parameters: the cluster delay spread, the cluster angular spreads, the number of paths within a cluster, and the number of clusters at each time instant. We observe significant *correlations between cluster parameters*, which can be used to considerably improve current channel models.

1. INTRODUCTION

Stochastic MIMO channel models based on physical considerations recently became important because they allow to model the spatial structure of the channel in a convenient way with low complexity. Prominent models are the COST 273 channel model [1], the 3GPP SCM model [2] and the WINNER channel models [3]. All these models use the concept of multipath clusters. Although the models provide "default parameters", they lack a convincing fit with measurement data [4]. Improved parameterization techniques are vital for the success of these models. We will show that especially the use of *correlated* cluster parameters can help to improve the model accuracy.

In this work we present a framework for identifying clusters from measurements without user intervention and propose a way to use them to parameterize cluster-based channel models. Section 2 gives a short overview of the parameters in the considered channel models. In Section 3 we introduce the framework for evaluating model parameters from measurements. We apply this framework on measurements, briefly described in Section 4. In Section 5 we discuss the resulting cluster parameter values and the importance of correlated cluster parameters. Finally, Section 6 concludes the paper.

2. GEOMETRY-BASED STOCHASTIC MIMO CHANNEL MODELS

Current geometry-based stochastic MIMO channel models such as the COST 273 or the WINNER channel model use the concept of multi-path clusters to model the radio channel. Clusters are defined as a group of multipath components (MPCs) showing similar parameters. Each MPC represents a unique link between the Tx and Rx (double-directional approach, see [5]), described by the complex path weight, delay, angle of departure (AoD), angle of arrival (AoA), and Doppler shift (not regarded in this paper). The radio channel is then modeled by a superposition of several clusters, each consisting of multiple MPCs.

To model a — representative — scenario these clusters are placed in either way, (i) in a specified geometry (euclidean coordinate space), or (ii) in parameter space (delay and angles). Both approaches are equivalent, having the parameters for one approach we can adopt them for the other. In this paper we use the parameter space.

Single MPCs within the clusters are placed randomly according to prespecified distributions. The parameters of these path distributions are the *spreads of the clusters* in delay, AoA, and AoD (i.e. the cluster's extent in space), the *number of paths* within a cluster, and the *number of coexisting clusters*. In the following we denote this set of parameters as *"cluster parameters"*. Since these parameters are used in the models to generate new clusters, at least both the mean and the standard deviation of the cluster parameters have to

This work was conducted within the European Network of Excellence for Wireless Communications (NEWCOM). We thank Elektrobit for supporting this work. This paper was supported by the Austrian Kplus program.

be specified. As the cluster parameters may depend strongly on each other [6], this correlation should also be taken into account in the models.

The cluster parameters are usually external model parameters that have to be specified by the user. Unfortunately, these parameters are not easy to extract from measurement data. In the following we will describe an approach to solve this problem.

3. PARAMETERIZATION FRAMEWORK

The models described in the previous section all come with some "default parameters". While path loss, global mean delay, and global delay spread can be estimated directly from measurements, *cluster* parameters are more difficult to extract, so some were empirically determined by educated guesses (e.g. variance of the cluster angular spread, dependence of angular spread on delay spread). We present a framework to estimate the cluster parameters directly from measurements.

The framework consists of following steps:

1. Conduct measurements in scenarios to be parameterized
2. Estimate discrete (coherent) propagation paths using a high-resolution parameter estimator
3. Cluster the propagation paths
4. Estimate cluster parameters
5. Estimate the *distribution* of the cluster parameters (in extension of our work in [7])

ad 2 — We used the Initialization-and-Search-Improved SAGE (ISIS) estimator on the measured impulse responses for every time instant to obtain coherent propagation paths for every position of the measurement route.

ad 3 — Using the clustering algorithm specified in [8] to automatically identify clusters for every time instant of the measurements.

ad 4 — For every cluster, we estimated the cluster power, the total power of the considered snapshot, the number of paths within a cluster, the number of coexisting clusters in the considered snapshot, the cluster mean delay, mean AoA, and mean AoD, the cluster rms delay spread, AoA spread and AoD spread. Note that when estimating the mean and variance of angular parameters, the ambiguity around $\pm\pi$ has to be taken into account.

ad 5 — We describe the *distribution of each cluster parameter* by its mean value, its standard deviation and its correlation with other cluster parameters. These values can be obtained by the well-known sample mean, sample variance and sample correlation estimators. Note that this corresponds to modelling the cluster parameters by one single (uncorrelated or correlated) multi-dimensional Gaussian distribution.

4. MEASUREMENTS

We conducted indoor MIMO wideband measurements at 2.55 GHz using an Elektrobit PropSound CS^{TM} channel sounder at the University of Oulu, Finland. Details about the sounder settings and antenna configuration can be found in [9, 7]. For the present paper we selected four particularly interesting routes in different environments, displayed in Figure 1, to compare the cluster parameters. The measurements were time variant (except for the "stationary" scenario), where we fixed the Rx while we moved the Tx along a route.

We decided to present three kinds of environments: (i) Different offices (see Figure 1b); the cluster parameters should be comparable, there. (ii) A cafeteria, (in Figure 1a (left), showing the cluster parameters in a large room. (iii) A laboratory scenario shown Figure 1a (right), which will serve as example, where the modelling approach fails.

5. RESULTS

We applied the presented framework to the measurement data and evaluated the cluster parameter distributions. In this paper we discuss the mean and standard deviation of the cluster parameters, and their correlations. Furthermore, we will show the impact on a model when neglecting the correlation parameters. Finally, we shall demonstrate under which conditions a cluster parameterization based on a single multidimensional Gaussian distribution fails.

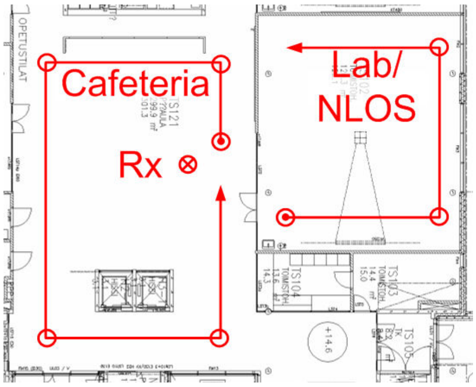
5.1. Cluster parameters

In Table 1 we provide the mean and standard deviations of the cluster parameters.

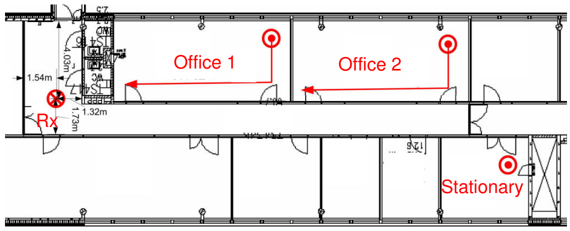
First we evaluated each measurement route individually. In the cafeteria we obtain a large number of clusters, which can be attributed to the (mostly) LOS link. Clusters can be well separated under these conditions. Clusters show large delay spread with strong variances, because of the large size of the room. The angular cluster spreads are around $10°$, where also the standard deviations are quite large. Because of the LOS link, the average cluster power is larger than in the other (NLOS) scenarios.

Both Office 1 and Office 2 show quite similar parameters. In Office 1, more clusters were identified, which is due to higher SNR and thus better resolution of clusters. Also the cluster delay spread values are slightly smaller for Office 1, since the route was closer to the Rx. Both angular cluster spread parameters (mean and standard deviation) are very similar, which accounts for the quite similar spatial structure of the channels.

The stationary measurements in the office shows quite different parameters because of the already high path loss. Only propagation paths approaching the Rx with AoAs from the



(a) Cafeteria (LOS) and Laboratory environment (NLOS)



(b) Office scenarios

Fig. 1. Measured scenarios: (a) Left: Cafeteria (room length ~ 9 m), metal tables and chairs, some people sitting at the tables; (a) Right: Laboratory environment, Rx in the Cafeteria; (b) Office rooms (room width ~ 4 m), amply furnitured

Table 1. Cluster parameters

	# clusters	# paths in cluster	cluster mean gain [dB]	mean cluster delay / ns	rms cluster delay spread / ns	rms cluster AoA spread / °	rms cluster AoD spread / °
Mean parameter values							
Cafeteria	13.8	7.8	-50.0	75.3	10.0	9.3	10.8
Stationary	7.3	3.8	-69.9	176.8	2.9	2.8	10.6
Office 1	10.2	12.0	-58.5	85.2	6.0	14.9	17.5
Office 2	7.9	14.0	-58.7	130.4	9.4	14.2	19.0
Offices	8.5	9.7	-62.6	131.1	5.9	10.4	15.5
Parameter spread values							
Cafeteria	4.3	6.6	7.6	32.5	11.1	8.7	9.2
Stationary	3.0	3.8	4.5	8.6	3.5	3.2	12.1
Office 1	4.7	7.4	5.0	12.0	2.6	8.8	10.3
Office 2	3.1	7.8	4.5	14.2	4.0	7.8	11.0
Offices	3.9	7.8	7.2	40.2	4.3	9.0	11.7

corridor were strong enough to be identified. Thus, the cluster angular spread around the Rx was very small. Also in the room we observe smaller cluster spreads. Note that also the number of paths within a cluster is significantly smaller than in other rooms.

Finally, we provide global parameters for the considered office environment, averaged over all scenarios. For this, we evaluated the cluster parameters for all office rooms jointly by evaluating the distribution parameters from all clusters in all office rooms. Note that the special propagation effects of the Stationary room are lost by this averaging. However this effect can be captured by taking the correlation of the cluster parameters into account.

Figure 2 provides the correlation coefficients between the cluster parameters for the averaged environment over all offices, where red colors denote strong positive correlation, blue colors denote negative correlations, and green color corresponds to uncorrelated values. First, we observe significantly more and stronger correlations than in a different environment [6].

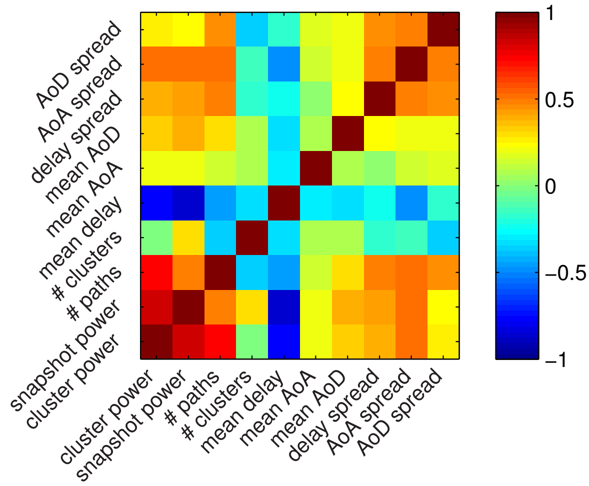


Fig. 2. Cross-correlation values for the global office parameters

We find that cluster power is positively correlated with the the number of paths within a cluster, which is intuitive since more paths can carry more power. We also observe a negative correlation between the cluster power and the cluster mean delay, which is physical, since paths coming with short delays carry more power. Also, all the spread parameters are positively correlated with each other. In contrast to an earlier publication [6] we also find correlations with the mean angular parameters indicating a dominant direction.

5.2. Impact on the model

We consider a simple cluster-based wideband MIMO channel model presented in [10]. We compare following ways to parameterize clusters. First, we draw cluster parameters from uncorrelated Gaussian distributions with means and variances obtained from Table 1. Second, we use a correlated Gaussian distribution to take correlations between cluster into account according to Figure 2. Third, for comparison, we use a sum of correlated Gaussian distributions, which corresponds to the Gaussian kernel density estimator (KDE) method presented in [10].

To validate the model parameterization, we use following approach: (i) generate reference channels using the estimated coherent reference paths, (ii) invoke the model and generate modelled channels using the selected parameterization (uncorrelated cluster parameters, correlated cluster parameters, KDE), (iii) compare the channels by using performance metrics.

In this paper we chose to generate 4×4 MIMO channels with 20 MHz bandwidth. The channels are compared using the mutual information (MI) [11], with constant Tx power and 10 dB (average) receive SNR. In the following we compare the MI cdf for the different parameterization approaches.

We observe the following properties of the different parameterization approaches:

- For single office rooms, cluster parameter correlation does not improve the model fit, because the correlations are too weak and the scenario does not change significantly (see Figure 3a). Even the KDE approach results in nearly the same fit.
- For averaging the office rooms, parameter correlation *significantly improves* the model fit. Especially power and delay are strongly correlated. This has to be taken into account for obtaining a good fit with measurement data (see Figure 3b). Using uncorrelated cluster parameters, the diversity of the channel is overestimated.
- For the cafeteria scenario, cluster correlation improves the model fit only slightly (see Figure 3c). Again, it fits the diversity of the channel better. Also this time the KDE parameterization results in a very good fit.
- When the underlying distribution of the parameters significantly differs from a single (correlated or uncorrelated) Gaussian distribution, the model does not fit any more. Figure 3d shows an example of such a scenario. Here, two dominant receive directions occur (from the lab and a significant backward reflection), which cannot be accounted for by the parameterization approach with a single Gaussian. When using the KDE approach (with only 10 kernels), the model already fits the measurements well.

6. CONCLUSIONS

We presented a framework to *automatically* obtain cluster parameters for geometry-based MIMO channel models from measurements. This allows to process large amounts of data in reasonable time. After applying this framework to data from an indoor MIMO measurement campaign we discussed the means and standard deviations of the cluster delay spread, the cluster angular spreads, the number of paths within a cluster, and the number of clusters within a snapshot.

We found that averaging to obtain global parameters for a diverse environment, removes particular properties of the spatial structure of the channel. This deficiency is present in all current models. By introducing correlations of the cluster parameters, the model fit can be significantly improved in certain scenarios.

However, for some scenarios, where the cluster parameters cannot be described by a single Gaussian distribution, more sophisticated cluster parameterization approaches are necessary.

7. REFERENCES

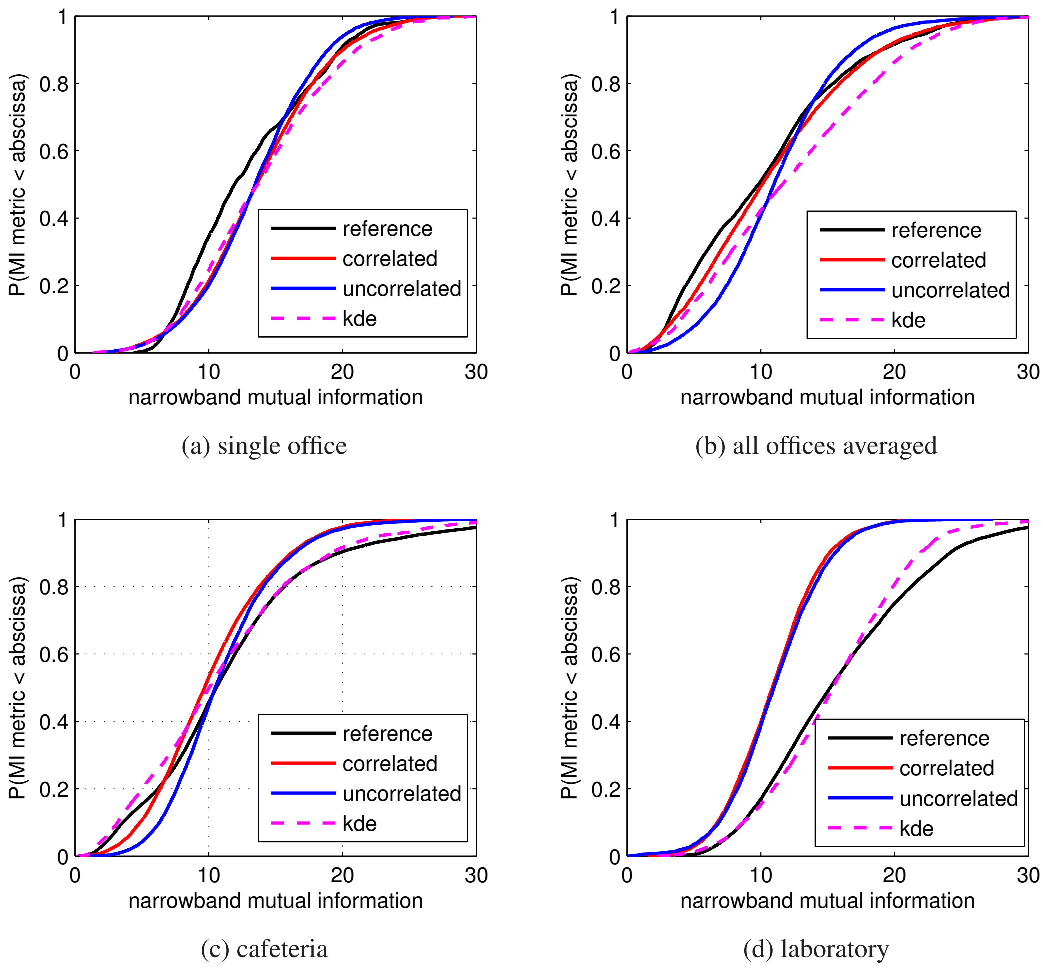
[1] L. Correia, Ed., *Mobile Broadband Multimedia Networks*. Academic Press, 2006.

[2] “Spatial channel model for Multiple Input Multiple Output (MIMO) simulations (3GPP TR 25.996), v6.1.0,” Sep. 2003. [Online]. Available: www.3gpp.org

[3] H. El-Sallabi, D. Baum, P. Zetterberg, P. Kyösti, T. Rautiainen, and C. Schneider, “Wideband spatial channel model for MIMO systems at 5 GHz in indoor and outdoor environments,” in *Proc. IEEE VTC’06 Spring*, Melbourne, Australia, May 2006.

[4] P. Kyösti, D. Laselva, L. Hentilä, and T. Jämsä, “Validating IST-WINNER indoor MIMO radio channel model,” in *IST Mobile and Wireless Summit 2006*, June 2006.

[5] 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.



(a) single office

(b) all offices averaged

(c) cafeteria

(d) laboratory

Fig. 3. Model fit for the various scenarios

[6] N. Czink, E. Bonek, L. Hentilä, P. Kyösti, J.-P. Nuutinen, and J. Ylitalo, "The interdependence of cluster parameters in mimo channel modeling," in *EUCAP 2006*, Nice, France, Nov. 2006.

[7] N. Czink, E. Bonek, L. Hentilä, J.-P. Nuutinen, and J. Ylitalo, "Cluster-based MIMO channel model parameters extracted from indoor time-variant measurements," in *IEEE GlobeCom 2006*, Nov. 2006.

[8] N. Czink, P. Cera, J. Salo, E. Bonek, J.-P. Nuutinen, and J. Ylitalo, "A framework for automatic clustering of parametric MIMO channel data including path powers," in *IEEE Vehicular Technology Conference 2006 Fall*, Montreal, Canada, 2006.

[9] E. Bonek, N. Czink, V. Holappa, M. Alatossava, L. Hentilä, J. Nuutinen, and A. Pal, "Indoor MIMO measurements at 2.55 and 5.25 GHz - a comparison of temporal and angular characteristics," in *IST Mobile Summit 2006*, Mykonos, Greece, June 2006.

[10] N. Czink, E. Bonek, L. Hentilä, J.-P. Nuutinen, and J. Ylitalo, "A measurement-based random-cluster MIMO channel model," in *IEEE Antennas and Propagation Symposium 2007, submitted*, Honolulu, USA, June 2006, available for download at http://www.nt.tuwien.ac.at/staff/nicolai-czink/.

[11] I. E. Telatar, "Capacity of multi-antenna gaussian channels," AT&T Bell Laboratories, Tech. Rep. BL0112170-950615-07TM, 1995.