51. IWK

Internationales Wissenschaftliches Kolloquium
International Scientific Colloquium

PROCEEDINGS 11-15 September 2006

FACULTY OF ELECTRICAL ENGINEERING AND INFORMATION SCIENCE

INFORMATION TECHNOLOGY AND ELECTRICAL ENGINEERING - DEVICES AND SYSTEMS, MATERIALS AND TECHNOLOGIES FOR THE FUTURE

Startseite / Index:
http://www.db-thueringen.de/servlets/DocumentServlet?id=12391

TECHNISCHE UNIVERSITÄT
ILMENAU

Impressum

Herausgeber: Der Rektor der Technischen Universität Ilmenau
Univ.-Prof. Dr. rer. nat. habil. Peter Scharff

Redaktion: Referat Marketing und Studentische Angelegenheiten
Andrea Schneider

Fakultät für Elektrotechnik und Informationstechnik
Susanne Jakob
Dipl.-Ing. Helge Drumm

Redaktionsschluss: 07. Juli 2006

Technische Realisierung (CD-Rom-Ausgabe):
Institut für Medientechnik an der TU Ilmenau
Dipl.-Ing. Christian Weigel
Dipl.-Ing. Marco Albrecht
Dipl.-Ing. Helge Drumm

Technische Realisierung (Online-Ausgabe):
Universitätsbibliothek Ilmenau
ilmedia
Postfach 10 05 65
98684 Ilmenau

Verlag:
Verlag ISLE, Betriebsstätte des ISLE e.V.
Werner-von-Siemens-Str. 16
98693 Ilrnenau

ISBN (Druckausgabe): 3-938843-15-2
ISBN (CD-Rom-Ausgabe): 3-938843-16-0

Startseite / Index:
http://www.db-thueringen.de/servlets/DocumentServlet?id=12391

51st International Scientific Colloquium
Technical University of Ilmenau
September 11-15, 2006

An Automatic Scheme for Clustering Simultaneously on Delay, Angle and Power Parameter Estimates of MIMO Channels

S. Nguyen, W. Kotterman, R. S. Thomä

Abstract

In this contribution, we describe a new automatic scheme for identifying clusters of channel parameters in radio channel measurement data, intended for modelling future Multiple-Input-Multiple-Output (MIMO) wireless communication systems. Such new multi-antenna systems promise significant increases in performance (with respect to capacity or Quality-of-Service) by actually taking advantages of the temporal and spatial dispersion of the radio transmission (the "channel") due to the constructive and destructive interference of scattered waves (called multi-path components, MPCs). For assessing the potential of MIMO systems, an accurate description of the dispersion on the channel is paramount. Recently, it was observed that the parameters of these MPCs are not evenly spread over parameter space but tend to be clustered. The proposed scheme clusters delay, azimuth angle, and power parameters of MPCs extracted from MIMO measurement data by maximum-likelihood methods. This scheme can identify various clusters, even when some overlap in the delay, Angle of Arrival (AoA), or Angle of Departure (AoD) domain. Outlier MPCs are rejected before clustering, and clustering results are smoothed over short-time intervals.

Our scheme was tested on simulation data from TU Ilmenau's proprietary channel modelling tool IlmProp [1] and on measured data. On the simulation data, the percentage of correct numbers and positions of cluster, with spreads within 5% accuracy, was better than 85% for different scenarios. The measured data were taken from three scenarios: Ilmenau city, Munich railway station, and Munich high-rise building. The results were promising without manual processing. Even when clusters overlapped in one or more dimensions, they were still separated and the strongest MPCs were always clustered.

I. Introduction

In mobile radio, we always encounter the effect of multi-path. The same transmitter signal can be multiply received by reflections or scattering from obstacles in the environment. Recent advances in multi-antenna MIMO research promise significant performance (capacity, Quality-of-Service) improvements by exploiting this multi-path. With enough independent scattering, multiple independent transmission links can be operated from the same antennas, theoretically only limited by number of antenna elements and the correlation between the antenna signals.

As reported in many papers [2] [3], typically, MPCs tend to arrive in clusters. The clustered distribution significantly affects the spatial correlation properties of the channel, and thereby, the performance gains of the MIMO system [4], [5]. Generally, the more MPCs are clustered (i.e., the less angular spread within clusters) the less MIMO capacity we can achieve. In channel modelling, the multi-cluster approach has been used in all new models (COST 259/273, IEEE-WLAN, 3GPP-3GPP2, and WINNER) to reproduce the clustered distribution of MPCs.

Therefore, correctly extracting parameters of clusters is necessary to analyse and model MIMO channels. But, there is only a general definition so far. In all papers, for example [2] [3], a cluster is defined as a group of MPCs whose parameters are very similar, while being quite distinct from MPCs of other clusters in at least one parameter. Consequently, there is some arbitrariness in clustering MPCs.

Until recently, the identification of clusters has been done by visual inspection of 2-D power profiles, such as delay versus angle of arrival, delay versus angle of departure. In the 2-D profiles, clusters are often overlapping and are difficult to separate because other data dimensions are ignored. When done

in 3-D, visual inspection becomes a real challenge. An automatic clustering scheme is required here, especially when processing large amounts of measured data.

In this article, we propose a new automatic scheme for identifying clusters using delay, azimuth angle, and power parameters of MPCs in MIMO channels. This scheme is performed in overlapped intervals of measurement instances in three sequential procedures: pre-, main-, and post-processing. In the pre-processing, outlier MPCs are removed from the data, in the main-processing, the data are clustered, and clustering results are smoothed in the post-processing procedure.
This article is organised as follows: in Section II we describe the problem and analyse encountered difficulties in automatic clustering. Clustering algorithms are introduced in Section III. Clustering validity measurements are also discussed here. Section IV analyses available automatic clustering schemes. Our proposed automatic scheme is described in Section V. Section VI presents clustering results on simulation and measurement data. Conclusions are drawn in Section VII.

II. The problem description

In order to measure the response of a MIMO channel, we use a MIMO channel sounder (e.g. RUSK [6]). From the measured data, parameters of MPCs (delay, azimuth and elevation angles, power…) are estimated by an estimator, such as ESPRIT or RIMAX [6].
The input data of the clustering problem are these estimated parameters. In this article, we cluster MPCs basing on the most important parameters for identifying clusters: delay, angle of arrival, angle of departure, and power. Both angles are only taken in azimuth, as the resolution in elevation of the measured data is poor. The output is a vector of cluster indexes of MPCs in all measurement instances.

Clusters of MPCs are only defined in general terms as in Section I. The clustering method is based on maximising intra-group similarity and minimising inter-group similarity. In that way, two bases of clustering are:

- Define a scalar distance function that includes all parameters to measure the proximity (similarity and dissimilarity) between data points.
- Choose a clustering algorithm whose result clusters fits best to the data.

When automatically clustering MPCs in MIMO channels, we encounter three problems:

- The data are multi-dimensional with different dimensions (of angle and delay). Distributions of mean delays and angles of clusters as well as of MPCs in a cluster are very different.
- Various clusters show sizes and shapes, with overlap anywhere in parameter domains due to (single and multiple) various scattering objects in the environments.
- Outlier MPCs appear randomly with short lifetimes. They may be the result of distributed scattering or phantom estimates due to noise. In many scenarios, they form a large portion of the total number of MPCs. Forcing outlier MPCs to belong to clusters distorts the shapes of these clusters, increases the span of the parameter domain, and changes measures of compactness and of separation of data. These affects cause wrong clustering results, especially with respect to the number of clusters.

III. Clustering criterions and algorithms

III. 1 Clustering algorithms

There are two well-known types of clustering algorithms: pair wise similarity-based clustering (e.g. hierarchical) and centroid-based clustering (e.g. K-means, fuzzy C-means). In our work, we decide to use centroid-based clustering algorithms because they are based on optimal theory and are tolerant to outliers [7]. Criterions and corresponding algorithms are described in the next sections.

Since parameters of MPCs are continuous, we choose the Euclidean distance as proximity measure between MPCs in parameter domains.

K-means clustering algorithm

K-means is the most popular centroid-based algorithm [7]. It tries to assign points to clusters so that the mean square distance of points to the centroid of the assigned cluster is minimised:

$$D(X,V) = \sum_{k=1}^{c} \sum_{i \in C_i} \| x_i - v_k \| = \sum_{k=1}^{c} \sum_{i \in C_i} D_{ik} \tag{1}$$

where X is the data set and V the centroid set of c clusters.

K-means is a *local optimal algorithm* based on the criterion (1) and is iteratively executed. The data model of this algorithm includes non-overlapped spherical clusters of similar size. It is a hard clustering algorithm, it means that a data point either does or does not belong to a cluster and created clusters are mutually exclusive in the iteration process.

The fuzzy clustering algorithms

Fuzzy clustering algorithms [8], in contrast to K-means, allow points to belong to several clusters simultaneously, with different degrees of membership. It means that overlapped clusters (as in MIMO channel) can be identified.

- **Fuzzy c-means algorithm** can be considered as a generalisation of the K-means clustering, it is a *global optimal algorithm* based on minimizing the objective function:

$$D(X,U,V) = \sum_{i=1}^{c} \sum_{k=1}^{N} (\mu_{ik})^m \| x_k - v_i \|^2 = \sum_{k=1}^{c} \sum_{i=1}^{N} (\mu_{ik})^m D_{ik}^2 \tag{2}$$

  Matrix U = $[\mu_{ik}]$ represents the fuzzy partitions, μ_{ik} is probability that x_k belongs to cluster i. Its conditions are given by:

$$\mu_{ik} \in [0, 1];\ 1 \le i \le c;\ 1 \le k \le N \tag{3}$$

$$\sum_{i=1}^{c} \mu_{ik} = 1;\ 1 \le k \le N \tag{4}$$

- **Gustafson-Kessel (GK) clustering algorithm** is an improvement on the fuzzy C-means algorithm by employing an adaptive distance norm. Each cluster has its own norm-inducing matrix A_k, which yields the distance function:

$$D_{ik}^2 = (x_k - v_i)^T A_i (x_k - v_i), \qquad i = 1,\ldots,c, \quad k = 1,\ldots,N \tag{5}$$

  The matrix A_i is calculated at each iteration step from the fuzzy covariance matrix [8].

  As a result, while the K-means or the fuzzy C-means algorithm assumes spherical clusters, this algorithm allows identifying ellipsoidal clusters. Various clusters in MIMO channels (Section II) can be fitted better with this improvement.

III.2 Determining the optimal clustering result (number of clusters and partitioning of MPCs to clusters)

Clustering algorithms require the number of clusters as an input parameter and have different results with different initial centroids. In order to determine the optimal number of clusters and partitioning, the multi-run approach is often used as follows:

- Run the algorithm for different initial centroids and numbers of clusters *c*
- Assess the goodness of the obtained partitions using a scalar validity measure and choose the optimum.

Many different clustering validity measures are described [7] [8], but none of them is universal. For a specific data set, we have to find an appropriate validity index and even modify it if necessary. We just describe here two used validity measures.

For data without overlapping clusters the mean of silhouette values of all points [7] is the preferred validity measure. This measure is in interval [-1, +1].

For data with overlapping clusters, validity measures should include membership coefficients. In our work, we modify Xie and Beni's (XB) index [8] to suit MPC data better.
The XB index is a "compactness over separation" measure, and defined as the ratio of the total variation within clusters (the compactness) and the minimum distance between the cluster centroids of clusters (the separation):

$$XB(c) = \frac{\sum_{i=1}^{c} \sum_{k=1}^{N} \mu_{ik}^{m} \left\| x_k - v_i \right\|^2}{N \min_{ij} \left\| v_j - v_i \right\|^2} \tag{6}$$

The optimal number of clusters should minimise this index.

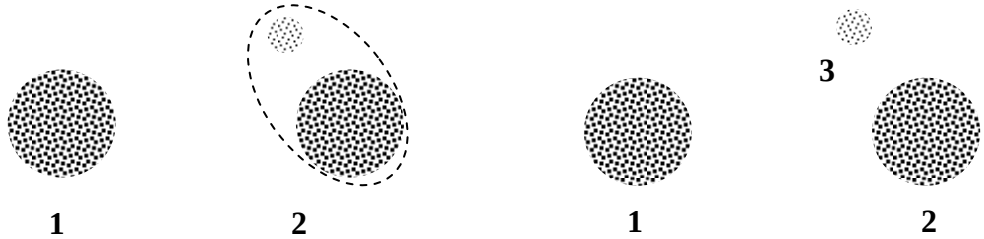

Figure 1: Clusters with different sizes and densities.
Left, two identified clusters when using XB validity index. Right, three clusters when using our modified version.

The separation is locally estimated instead of globally, thereby it is only appropriate in case clusters are about the same size and near-uniformly distributed (the data model of fuzzy c-means algorithm). In case a small cluster is close to a larger one, such as in Figure 1, the index causes a wrong choice of the number of clusters.

In order to overcome this problem, we propose a modified XB index that uses the sum of the shortest distances between centroids instead of the minimum of them as the separation measure. In addition, we also modified the compactness measure of each cluster as the sums of membership-weighted mean radii of clusters:

$$XB(c) = \frac{\sum_{i=1}^{c} \left(\frac{\sum_{k=1}^{N} \mu_{ik}^{m} \left\| x_k - v_i \right\|^2}{\sum_{k=1}^{N} \mu_{ik}^{m}} \right)}{N \sum_{i=1}^{c} \min_{\substack{ij \\ j \neq i}} \left\| v_j - v_i \right\|^2} \tag{7}$$

Both the XB index and our modified index are evaluated on simulation data from IlmProp in Section VI.

IV. Available automatic clustering schemes

There are a few automatic clustering schemes available so far [9], [10], [11].

Salo and Czink proposed a semi-automatic scheme in [9] using three parameters: delay, angle of arrival azimuth, and angle of departure azimuth. The 3-D problem was performed in three sequential 1-D steps. Because of this independent sequence, it tends to split some clusters or combine others. The authors also tried a 1-D step followed by a 2-D step, where 1-D delay clustering was followed by a 2-D Angle of Arrival−Angle of Departure clustering of each delay cluster. But the differences between the two schemes were found to be insignificant [9].

A better scheme was proposed in [11] by Czink. In contrast to the previous scheme, it clusters simultaneously on three parameters as above and included the power parameter. Its important features are:

- *A 3-D clustering procedure in the domain of delay, angle of arrival azimuth, and angle of departure azimuth parameters, using the Multi-path Component Distance (MCD) as distance metric*:

$$MCD = \sqrt{\left(d_R^2 + d_T^2 + (\xi.d_\tau)^2\right)} \tag{8}$$

  Parameters are normalised so that maximal distances in all dimensions are 1. The distance between two angles is measured by distance between two corresponding points on the unit circle. For delay, in addition to the normalisation, the distance is scaled with the normalised delay spread ($\tau_{std} / \Delta\tau_{\max}$). After normalisation, since the sizes of clusters in the delay parameter often are still much smaller than in the angular parameters, delay has to be weighted again. The extra weighting varies with the scenarios and can be spatial-variant. For example, in [10], its value is set to 10 (ζ = 10) for the particular scenario in this paper. The extra weighting is based only on visual inspection of the clustering results without any calculation.

- *Using power weighting in K-means clustering algorithm*. MPC' powers are used as weighting coefficients for data in the centroid calculating equation (in every iteration step). This power-weight pulls the centroids to strong power points, believed to represent the important scattering areas.

V. The proposed automatic clustering scheme

V.1 Overview of the proposed scheme

Our proposed scheme is based two observations of MPC data:

- MPCs are often better clustered in the angular domain than the delay domain. While there can be many clusters that show approximately the same delay but are different in angles (e.g.: single scattering objects are on an ellipse whose two foci are at positions of the transmitter and the receiver), only a few clusters have approximately the same angles but are different in delay.
- The dynamic range of delay in clusters in delay is often much smaller than that in clusters in angles.

From these observations, we propose a "hybrid" two-stage scheme between the sequential and simultaneous schemes described in Section IV as follows:

- **Cluster in the delay-times-angle 2-D domain**

  MPCs are mapped onto a multiplied 2-D data domain (delay times angle of arrival, delay times angle of departure) before being clustered.

  Generally, the parameters of MPCs in a cluster are very similar, resulting in the delay-times-angle parameters of MPCs in a cluster being very similar too**.** Clusters that have approximately the same angles but are different in delay are now separated in the multiplied domain. However, a cluster in the multiplied domain may be a group of some true clusters, since a parameter can compensate another in the multiplication (if $x_1 \approx k \times x_2$ and $y_1 \approx y_2/k$ then $x_1 \times y_1 \approx x_2 \times y_2$). For this reason, we need an additional stage to separate these "complex" clusters.

- **Identify and separate "complex" clusters**

  Caused by the compensation, "simple" clusters in a "complex" cluster are normally separated in the original parameters, especially in scenarios with small relative spread in delay within clusters (modelled in 3GPP2 SCM [12] and WINNER models [13]). The identification is

made in both the angular and delay domain, and then, the separation is performed either in the delay or angular domain.

There is a problem when clustering in angular as well as in delay-time-angle domains: angles are periodic variables. Because of the localisation in clustering, this problem occurs only around angles of 0^0 and 180^0. One solution to this is to rotate the axes, such that the density of MPCs is minimised (or null) at these angles

By the proposed mapping, we can include delay information in the angular domain without weighting, and the first stage can be now considered as clustering in a 2.5-D domain. The second stage is thus considered as (3-2.5=) 0.5-D clustering. Consequently, we name this scheme "2.5-D+0.5-D" clustering.

In order to increase reliability of the clustering, data are processed in measurement intervals instead of in only one instance; the interval length depends on the degree of stationarity of the channel over time. Its advantages are:

- With an appropriate length, the compactness of clusters is increased while their separations remain constant.
- The stability over time of a cluster can be evaluated by the number of instances M in which this cluster is active (having at least N MPCs). We can define a stability threshold by a value set of (M, N), and reject clusters that do not satisfy it.
- Some sudden changes of clustering results can be smoothed when intervals are sufficiently overlapping.

Our scheme includes three sequential procedures: pre-processing, main processing, and post-processing.
The goal of the pre-processing is to remove outlier MPCs from input data. In fact, this is a copy version of the main-processing.
The main-processing will be described in the next section.

In the post-processing procedure, due to the overlap and the small time shift between consecutive measurement intervals, we can repair sudden changes in the number of clusters by a median filter on three consecutive intervals and re-cluster with the corrected number of clusters.

V.2 The main processing procedure

As above described, the main processing is performed in two stages:

- **Cluster in the delay times angle 2-D domain.**

  The data are mapped into the multiplied domain, and then, are clustered with different numbers of clusters (in a predefined range) by a modified fuzzy clustering GK algorithm. As proposed in [11], the power weighting is applied in the centroid calculation of the GK algorithm to pull centroids to strong power points. Our modified XB validity index (Section III.2) is used to select the optimal clustering result (corresponding to the minimal value of the index).
  For the obtained clusters, we reject clusters that do not satisfy the stability threshold, and their MPCs are marked as (short-time) outliers.

- **Identify and separate "complex" clusters and prune outlier MPCs causing by distributed scattering**.
  After the first stage, an identified cluster is:
  - A "simple" cluster: the angle-times-delay as well as original parameters of included MPCs are very similar, or
  - A "complex" cluster: can include one or some "simple" clusters and outlier MPCs that are closer to the centroid of this cluster than to that of other clusters.

If in the identified clusters, groups of MPCs exist then they are well separated, so we use K-means algorithm with silhouette thresholds that are close to the maximum value (1) to perform separation of the different groups and removal of outliers.

i. In both delay and angular domains, data in the considered cluster are clustered. The optimal number of clusters corresponds to the minimal value of the silhouette index (the search range is set to [2, 4]). The separation is only valid if at least one of the identified groups is stable enough over the interval.
   - If the number of groups is the same in two domains, the thresholds are 0.8 and 0.9. We take the clustering result in the domain in which the silhouette value is higher.
   - If the number of groups is different in two domains, both thresholds are 0.9. We take the clustering result in the domain in which the number of groups is higher.

ii. The newly formed clusters are also checked on stability

VI. Results

In this section, we give results on simulation data from the IlmProp tool and on measured data, also from TU Ilmenau.

Parameters of our scheme are: the number of measurement instances in an interval is 6, and the sliding step is half the length of the interval so that the current interval includes the second half of the previous interval and the first half of the next interval. This choice improves reliability when applying the median filter to smooth the numbers of clusters in three consecutive measurement intervals. The range of numbers of clusters is set to [2, 20] (empirical values). The stability threshold of a cluster is at least (N=) 2, 3, or 4 MPCs per cluster per measurement instance in (M=) 4, 3, or 2 measurement instances respectively.

The IlmProp is a flexible directional channel model for multi-user time variant frequency selective MIMO systems [1]. We use an available exemplary geometry called “template1”, which includes 8 fixed clusters and 1 obstacle (all reflections are single-bounce). The simulation is made over 256 different positions; the transmitter moves while the receiver is fixed (Figure 2). This geometry is ideal in the sense that it produces no outlier MPCs.

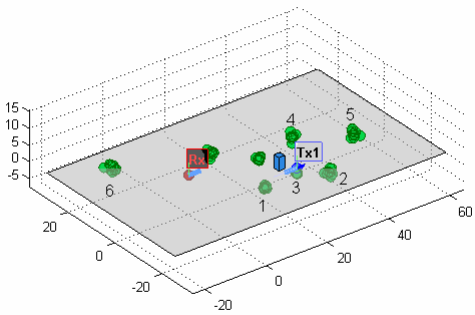

Figure 2: Geometry of the simulation data

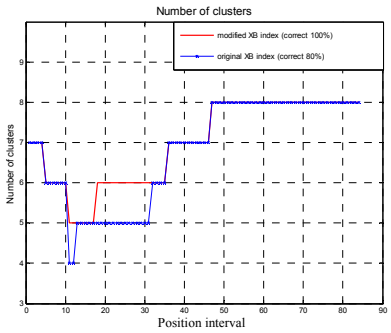

Figure 3: Number of clusters with the XB index (80%) and our modified version (100% correct)

When using the original XB index (6), the numbers of identified clusters was wrong in about 20% of interval (between 10th and 30th interval in Figure 3) in which clusters were not of similar size and were uniformly distributed (as in Figure 1, section III.2). With our modified XB index (7), the number and positions were correct (temporal and angular spreads within 5%) in all intervals. Figure 3 illustrates this improvement in the number of identified clusters.

Extending this template to a more real scenario, following [14], we added outlier MPCs that were characterised by randomly varying delay, angle of arrival, and angle of departure. The lifetimes of outlier MPCs were also random. The mean ratio of outlier/clustered MPCs in a measurement instance was about 15%. The numbers of clusters were correct in more than 90% of all intervals, and the

spreads of clusters were within 5% in more than 85% of all intervals. An illustration of a comparison of the measured and clustered delay spreads is showed in Figure 4.

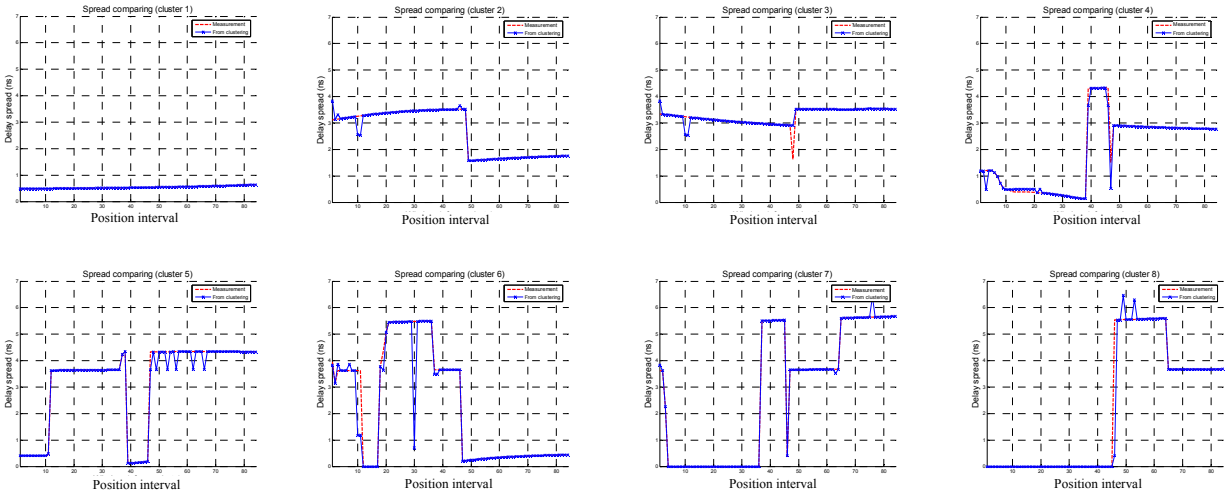

Figure 4: Comparison delay-spreads between measurement and after clustering (8 clusters in Figure 2)

The measurements were performed using the RUSK MIMO channel sounder of MEDAV with carrier frequency 5.2 GHz and bandwidth 120 MHz [6]. The parameters of the MPCs were estimated by the high-resolution parameter estimation algorithm RIMAX [6]. The measured data were taken from three scenarios: Ilmenau city, Munich railway station, and Munich high-rise building.

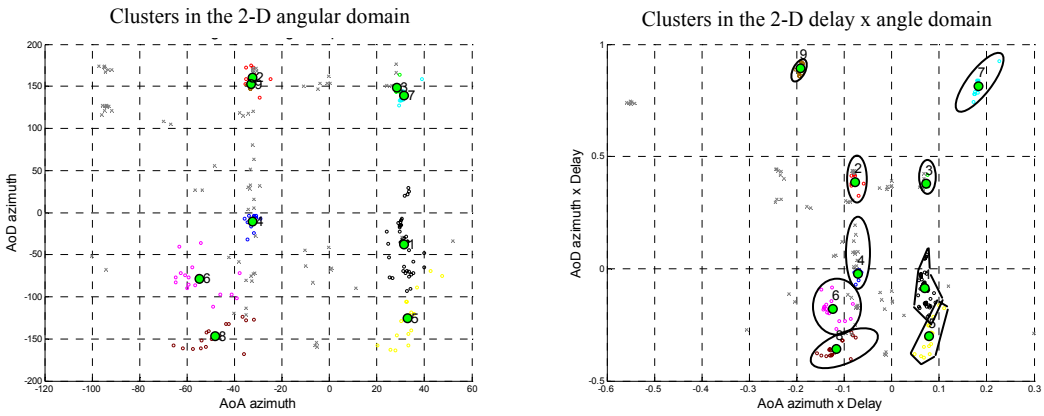

Figure 5: Clusters in the 2-D angular and the 2-D delay-time-angle domain

The effect of including delay information into the angular domain by mapping onto the delay-times-angle domain is showed in Figure 5. Clusters 2 and 9, 3 and 7 were very close and overlapped another in the angular domain but were clearly separated in the 2-D delay-times-angle domain.

Each scenario has different specific features. In the Ilmenau city scenario, clusters were overlapped in many measurement intervals, 70%-80% of all estimated MPCs were clustered, representing about 80%-90% of the total received power. In Munich high-rise building and Munich railway station scenarios, clusters were rather clearly separated, fewer MPCs were clustered, (less than 60% in the first scenario and 40% in the second scenario) but still the majority of the total power was clustered (60%-90%). In Munich railway station scenario, there were many clusters, which were often small (i.e. with not so many MPCs and low spreads) and were near-uniformly distributed over the environment.

In all scenarios, even when some clusters overlapped in one or more dimensions, they were still separated. Most MPCs in a cluster had approximately the same power and the strongest MPCs were always clustered.

VII. Conclusion

The contributions of this article are an automatic scheme for identifying clusters in the temporal (delay) and angular (angle of arrival, and angle of departure) domain, including the power. The data are processed in overlapping intervals of measurement instances. By clustering in the 2-D data domain of delay-times-angle of arrival and delay-times-angle of departure, and then separating "complex" clusters, this scheme overcomes the problem of weighting the different dimensions of delay and angle. The power weighting is applied in the centroid calculation of the Gustafson-Kessel fuzzy clustering algorithm. The Xie and Beni's validity index is modified to be better suited to selecting the optimal clustering result in multi-path component (MPC) data. As a result, various clusters can be identified, even when some overlap. Short-lived clusters are rejected by checking their stability over the interval. The reliability of the clustering is improved by applying a pre-processing procedure that removes most outlier MPCs from the data and a post-processing procedure that repairs sudden changes in the number of clusters by a median filter in over three consecutive intervals.

Our proposed scheme was tested on simulation data from the channel model tool IlmProp and on measured data, also from TU Ilmenau. For ideal simulation data without outlier MPCs, 100% of the numbers and positions of clusters were correct and all the spreads remained within 5% accuracy. In case of simulation data with outlier MPCs, this percentage was 80%-95%. The measured data were taken from three scenarios: Ilmenau city, Munich railway station, and Munich high-rise building. The results were promising, without any manual processing.

ACKNOWLEDGMENTS

We would like to thank the colleagues of Technical University Ilmenau and MEDAV GmbH for their support with data acquisition and for many valuable discussions.

References

[1] http://tu-ilmenau.de/ilmprop
[2] Molisch, F., "A Generic Model for MIMO Wireless Propagation Channels in Macro- and Microcells," IEEE Trans. Signal Proc, vol. 52, no.1, pp.61-71, Jan. 2004.
[3] Molisch, F., "Effect of Far Scatterer Clusters in MIMO Outdoor Channel Models," IEEE Vehicular Technology Conference (VTC), ISSN: 1090-3038, Vol. 1, pp. 534-538, Apr. 2003.
[4] Zetik, R.; Schneider, C.; Thomä, R., "Correlation between MIMO Link Performance Evaluation Results and Characteristic Channel Parameters," IST Mobile & Wireless Communications, Jun. 2004.
[5] Tang, Z.; Mohan S., "Impact of Clustering in Indoor MIMO Propagation Using Hybrid Channel Model," EURASIP Journal on Applied Signal Processing 2005:11, 1698-1711.
[6] Trautwein, U.; Landmann, M.; Sommerkorn, G.; Thomä, R., "System-Oriented Measurement and Analysis of MIMO Channels," COST 273 TD(05) 063, Bologna, Italy, Jan. 2005.
[7] Jain, K.; Dubes, C., "Algorithms for Clustering Data," Prentice Hall, 1988.
[8] Hoeppner, F.; Klawonn, F.; Kruse, R.; Runkler T., "Fuzzy cluster analysis," John Wiley & Son Ltd, 1999.
[9] Salo, J; Salmi, J.; Czink, N.; Vainikainen, P., "Automatic Clustering of Nonstationary MIMO Channel Parameter Estimates, " in Proc. Conference Proceedings of the 12th International Conference on Telecommunications, Cape Town, Sound-Africa, May, 2005.
[10] Czink, N.; Cera, P.; Salo, J.; Bonek, E.; Nuutinen, P.; Ylitalo, J., "Automatic Clustering of MIMO Channel Parameters Using the Multi-Path Component Distance Measure," IWS 2005, Aalborg, Denmark.
[11] Czink, N.; Cera P., "A novel framework for clustering MIMO channel data including MPC powers," Post-COST 273 Meeting, Lisbon, 2006.
[12] 3GPP TR 25.996, "3rd Generation Partnership Project; technical specification group radio access network; spatial channel model for MIMO simulations (release 6)," V6.1.0.
[13] IST-WINNER D5.4 Baum, S.; El-Sallabi, H.; et al., "Final Report on Link and System Level Channel Models," ver 1.4, Sep. 2005.
[14] Galdo, G.; Czink, N.; Haardt, M., "Cluster spatial localisation from high-resolution parameter estimation," in Proc. International ITG/IEEE Workshop on Smart Antennas (WSA), (Günzburg, Germany), Mar. 2006.

Authors:

Thanh Son Nguyen, M.Sc.
Wim Kotterman, Ph.D.
Prof. Dr.-Ing. habil. Reiner S. Thomä
Ilmenau University of Technology, Electronic Measurement Research Laboratory, P.O.B. 100565
98684 Ilmenau, Germany
Phone: +49 (0) 3677 69 3722 Fax: +49 (0) 3677 69 1113
E-mail: { Thanh-Son.Nguyen, Wim.Kotterman, Reiner.Thomae} @tu-ilmenau.de