TRACKING TIME-VARIANT CLUSTER PARAMETERS IN MIMO CHANNEL MEASUREMENTS

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***Abstract*— This paper presents a joint clustering-and-tracking framework to identify time-variant cluster parameters for geometry-based stochastic MIMO channel models.**

The method uses a Kalman filter for tracking and predicting cluster positions, a novel consistent initial guess procedure that accounts for predicted cluster centroids, and the well-known KPowerMeans algorithm for cluster identification.

We tested the framework by applying it to two different sets of MIMO channel measurement data, indoor measurements conducted at 2.55 GHz and outdoor measurements at 300 MHz. The results from our joint clustering-and-tracking algorithm provide a good match with the physical propagation mechanisms observed in the measured scenarios.

I. Introduction

In order to validate algorithms that exploit the opportunities offered by MIMO systems, MIMO channel models that are accurate, yet tractable are in high need. A promising approach involves cluster-based MIMO channel models [1]. As a matter of fact, the majority of standardized MIMO channel models, like 3GPP-SCM [2], IEEE 802.11n [3], COST 259 DCM, and COST 273 [4] are cluster based.

In measured MIMO channels the multipath components (MPCs) tend to occur in clusters, i.e., groups of MPCs with similar parameter values such as delay, directions of arrival (DoA) and directions of departure (DoD) [5], [6], [7]. It was shown in [8], [9] that channel models disregarding clustering effects overestimate the channel capacity.

In order to consistently parameterize recent cluster-based MIMO channel models [10], the clusters must be identified and parameterized from measurements. Initially, cluster identification was done visually [11], [6], [7], but this procedure is cumbersome and tiring for a large amount of measurement data, for multi-dimensional parametric data it becomes impossible. Moreover, visual clustering lacks a clear definition of what is a cluster. Thus, automatic cluster identification algorithms for parametric MIMO channels were developed [12], [13], [14]. These algorithms were all designed to identify clusters in individual time instants, and did not address the issue of cluster tracking over time. Since clusters can be used to model time-variant scenarios as well, a consistent approach is required for joint cluster identification-and-tracking over time. A simple cluster tracking algorithm was presented in [15], but it did not take joint clustering and tracking into account. An alternative method is to track individual paths directly in the impulse response [16].

In the present work we develop a joint clustering-and-tracking framework that uses (i) a Kalman filter [17] to track and predict cluster positions together with (ii) a new initial-guess procedure allowing to include the prediction of the Kalman filter, and (iii) the KPowerMeans clustering algorithm using the MCD distance metric [13] to identify clusters. To test the framework we used two different sets of time-variant MIMO channel measurements, one indoor environment showing rich scattering, and an outdoor environment showing few, very distinct propagation paths and many weak scattered paths. We found that this framework enabled to extract the cluster characteristics from time-variant MIMO channel measurements consistently.

The paper is organized as follows: Section II will describe the problem and introduce the parameters used. In Section III we provide a comprehensive description of the joint clustering-and-tracking framework. Results from applying the framework to the measurement data are presented in Section IV. Finally, we conclude the paper in Section V.

II. Problem description

Like in existing clustering applications, the starting point is a large number of measurements with a MIMO channel sounder. The parameters of the MPCs are estimated from the measured impulse responses using a high-resolution algorithm, e.g. SAGE, for each snapshot, individually.

In standard clustering, each snapshot is clustered independently [18], [13], and the clusters might be tracked afterwards [14]. The problem to solve is how to combine clustering and tracking in order to improve the clustering performance and to consistently track clusters.

We consider N data windows, $n = 1 \dots N$, each with a number of $L^{(n)}$ MPCs, where every single MPC is represented by its power $P_l^{(n)}$, $l = 1 \dots L^{(n)}$, and a parameter vector $\mathbf{x}_l^{(n)} = [\tau_l^{(n)}\ \varphi_{\mathrm{AoA},l}^{(n)}\ \varphi_{\mathrm{AoD},l}^{(n)}]^{\mathrm{T}}$ containing the delay, azimuth AoA and azimuth AoD, respectively. The data for all paths are collected in the power vector $\mathbf{P}^{(n)} = [P_1^{(n)} \dots P_L^{(n)}]^T$ and the matrix $\mathbf{X}^{(n)} = [\mathbf{x}_1^{(n)} \dots \mathbf{x}_L^{(n)}]^T$.

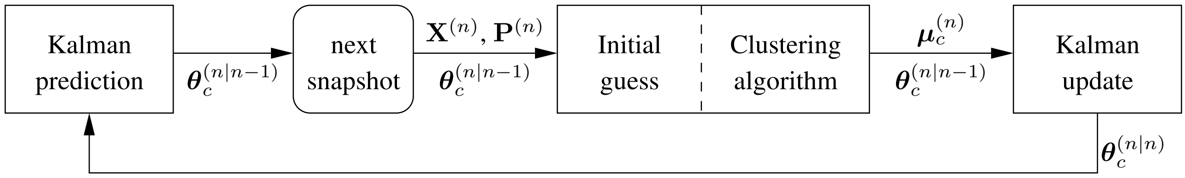

Fig. 1. Clustering framework: Clusters with parameters $\boldsymbol{\theta}_c^{(n)}$ are identified and tracked in the input data $(\mathbf{X}^{(n)}, \mathbf{P}^{(n)})$, the Kalman filter updates the cluster parameters, the prediction provides an input to the initial guess.

Each *cluster* is determined by following parameters:

1. A *unique cluster-ID* c.
2. The *cluster power* at time n. Denoting the set of path indices belonging to cluster c at time snapshot n by $\mathcal{I}_c^{(n)}$, the cluster power is calculated as $\gamma_c^{(n)} = \sum_{l\in\mathcal{I}_c^{(n)}} P_l^{(n)}$.
3. The *number of paths* within the clusters $L_c^{(n)} = |\mathcal{I}_c^{(n)}|$, where every path is assumed to belong to one cluster, uniquely.
4. The *cluster centroid* position in the angle-angle-delay domain $\boldsymbol{\mu}_c^{(n)}$. The cluster centroid position can be calculated as

$$\boldsymbol{\mu}_c^{(n)} = [\tau_c^{(n)} \ \varphi_{\mathrm{Rx},c}^{(n)} \ \varphi_{\mathrm{Tx},c}^{(n)}]^{\mathrm{T}} = = \frac{1}{\gamma_c^{(n)}} \cdot \begin{bmatrix} \mathrm{angle}(\sum_{l\in\mathcal{I}_c^{(n)}} P_l^{(n)} \exp(j\cdot\varphi_{\mathrm{Rx},l}^{(n)})) \\ \mathrm{angle}(\sum_{l\in\mathcal{I}_c^{(n)}} P_l^{(n)} \exp(j\cdot\varphi_{\mathrm{Tx},l}^{(n)})) \\ \sum_{l\in\mathcal{I}_c^{(n)}} P_l^{(n)} \tau_l^{(n)} \end{bmatrix}, \quad (1)$$

where the mean angle is calculated by averaging angles over their respective complex representation.
For tracking, also the centroid speed is of interest, so we combine the position and speed in the cluster tracking parameter vector $\boldsymbol{\theta}_c^{(n)} = [\tau_c^{(n)} \ \Delta\tau_c^{(n)} \ \varphi_{\mathrm{Rx},c}^{(n)} \ \Delta\varphi_{\mathrm{Rx},c}^{(n)} \ \varphi_{\mathrm{Tx},c}^{(n)} \ \Delta\varphi_{\mathrm{Tx},c}^{(n)}]^{\mathrm{T}}$.
5. The *cluster's joint spread* $\mathbf{C}_c^{(n)}$, which is the power-weighted covariance matrix of the path parameters within one cluster at time n. The main diagonal contains the cluster spreads of the individual dimensions, i.e. the cluster delay spread, the cluster AoA spread and the cluster AoD spread. The off-diagonal elements describe the correlation between these spreads.
The cluster spread matrix is calculated by

$$\mathbf{C}_c^{(n)} = \frac{\sum_{l\in\mathcal{I}_c^{(n)}} P_l^{(n)} (\mathbf{x}_l^{(n)} - \boldsymbol{\mu}_c^{(n)})(\mathbf{x}_l^{(n)} - \boldsymbol{\mu}_c^{(n)})^{\mathrm{T}}}{\gamma_c^{(n)}}. \quad (2)$$

Note that in this equation, whenever adding or subtracting angles, the result must be mapped to the principal value in the interval of $(-\pi, \pi]$, which can be achieved easily by the operation

$$\mathrm{pv}(\varphi) = \mathrm{angle}(\exp(j\varphi)). \quad (3)$$

Based on this cluster data model, we will now introduce the clustering-and-tracking framework.

III. FRAMEWORK

For each time snapshot, the following steps are performed (see Figure 1):

1. A Kalman filter [17] both tracks the cluster position over time, and predicts the cluster position in the next snapshot.
2. The initial-guess routine provides a trustworthy initial guess of the cluster centroids, taking the predicted cluster centroids into account.
3. The clustering algorithm identifies clusters in the measurement data based on the initial guess.

A. Kalman cluster tracking

1) State-space model: For the Kalman tracking [17], only the cluster centroid position $\boldsymbol{\theta}_c$ is used. We use the following state equation

$$\boldsymbol{\theta}_c^{(n)} \quad = \quad \Phi\boldsymbol{\theta}_c^{(n-1)} + \mathbf{w}^{(n)}, \quad (4)$$

where $\mathbf{w}^{(n)}$ denotes the state-noise with covariance matrix $\mathbf{Q}$, and Φ is the state-transition matrix given by

$$\Phi = \mathbf{I}_3 \otimes \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix},$$

where identity matrices are denoted by $\mathbf{I}_d$ with d denoting the dimension, and $\otimes$ denotes the Kronecker matrix product.

Since we can observe only the cluster centroids and not their speed, we use following observation model

$$\boldsymbol{\mu}_c^{(n)} \quad = \quad \mathbf{H}\boldsymbol{\theta}_c^{(n)} + \mathbf{v}^{(n)}, \quad (5)$$

where $\boldsymbol{\mu}_c^{(n)}$ describes the *observed* cluster centroid position, thus $\mathbf{H}$ is given by

$$\mathbf{H} = \mathbf{I}_3 \otimes [\ 1 \quad 0\ ], \quad (6)$$

and $\mathbf{v}^{(n)}$ denotes the observation noise with covariance matrix $\mathbf{R}$.

2) Tracking equations: The derivation of the Kalman filter is straight-forward and leads to following prediction and update equations[1]

Prediction:

$$\boldsymbol{\theta}_c^{(n|n-1)} = \Phi\boldsymbol{\theta}_c^{(n-1|n-1)} \quad (7)$$

$$\mathbf{M}^{(n|n-1)} = \Phi\mathbf{M}^{(n-1|n-1)}\Phi^{\mathrm{T}} + \mathbf{Q} \quad (8)$$

Update:

$$K^{(n|n)} = \mathbf{M}^{(n|n-1)}\mathbf{H}^{\mathrm{T}}(\mathbf{H}\mathbf{M}^{(n|n-1)}\mathbf{H}^{\mathrm{T}} + \mathbf{R})^{-1} \quad (9)$$

$$\boldsymbol{\theta}_c^{(n|n)} = \boldsymbol{\theta}_c^{(n|n-1)} + K^{(n|n)}(\boldsymbol{\mu}_c - \mathbf{H}\boldsymbol{\theta}_c^{(n|n-1)}) \quad (10)$$

$$\mathbf{M}^{(n|n)} = (\mathbf{I} - K^{(n|n)}\mathbf{H})\mathbf{M}^{(n|n-1)} \quad (11)$$

3) Cluster association: A major problem in multi-target tracking is how to associate the predicted with the identified cluster centroids. Usually, such an association is based on the Euclidean distance in parameter space. Since we are tracking clusters that show a certain extent in parameter space, we use following probability-based method:

- The distance between a cluster with parameters $(\boldsymbol{\mu}_c,\ \mathbf{C}_c)$ and a cluster centroid $\tilde{\boldsymbol{\mu}}$ is defined by

$$\mathcal{G}_c(\tilde{\boldsymbol{\mu}}|\boldsymbol{\mu}_c, \mathbf{C}_c) = \frac{1}{(2\pi)^{3/2}\,|\mathbf{C}_c|^{1/2}} \cdot \cdot \exp\left(-\frac{1}{2}(\tilde{\boldsymbol{\mu}} - \boldsymbol{\mu}_c)^{\mathrm{T}}\mathbf{C}_c^{-1}(\tilde{\boldsymbol{\mu}} - \boldsymbol{\mu}_c)\right). \quad (12)$$

  Since a small distance between the two centroids now corresponds to a large value of this function, we refer to it as the *closeness function*.
- The closeness function is evaluated between all predicted and all new cluster centroids in both directions, i.e. between the old and the new centroids using the old covariance matrix, and between the new and old cluster centroids using the new covariance matrix.
- For each old cluster we determine the closest new cluster by finding the maximum value of the closeness function, and vice versa, for each new cluster we determine the closest old cluster in the same way.
- Whenever these two clusters are closest mutually, these two clusters are associated and being considered as the *tracked* cluster.
- Clusters that were not associated from the old snapshot stop to exist, clusters that were not associated from the new snapshot are considered as new clusters.

B. Cluster initial guess

A crucial point in any iterative clustering algorithm is the initial guess of the cluster centroids. Our new method chooses the centroids by maximizing the distances between them. In the following we will present how to choose the initial-guess centroids $\hat{\boldsymbol{\mu}}_c$.

1. Initialization:
   - No cluster prediction available:
     The first centroid $\hat{\boldsymbol{\mu}}_1$ is chosen as the path having strongest power.
   - Cluster Prediction available:
     Copy the initial-guess centroids from the predicted values
2. Calculate a weighted distance between any path and all (initial-guess) centroids using the multipath component distance (MCD) [19] by

$$D(\mathbf{x}_l^{(n)}, \hat{\boldsymbol{\mu}}_c) = \log_{10}(P_l^{(n)}) \cdot \mathrm{MCD}(\mathbf{x}_l^{(n)}, \hat{\boldsymbol{\mu}}_c).$$

   This leads to an $l \times c$ distance matrix $\mathbf{D}$ for every snapshot n. Here, the MCD is log-power weighted.
3. From these paths we select the one which has the maximum minimum distance to any centroid, i.e. $l = \arg\max[\min_c \mathbf{D}]$, where $\arg\max[\cdot]$ returns the index of the maximum element.
4. Reallocate all paths to their closest centroid (as in the KPowerMeans algorithm) and calculate the cluster power. Note that, in this case, the power-weighted MCD is also used but the powers contribute linearly.
5. If the maximum number of clusters was not reached, and all centroid powers are larger then 1% of the total snapshot power, then repeat from Step 2.
   Else discard the last centroid and stop. This algorithm leads to a trustworthy identification of the number of clusters.

C. Clustering algorithm

We use the KPowerMeans clustering algorithm presented in [13] with following modifications: (i) we apply the initial guess as described above, (ii) since the initial guess is deterministic, the algorithm is performed only once.

Should the outcome result in clusters carrying less than 1% of the snapshot power, the result is discarded and the procedure is restarted with the initial guess, but reducing the maximum number of clusters by one. Note that in this algorithm the existence of singletone clusters is possible, as long as they show enough power. In this way we can also account for strong, far reflections.

IV. Results

We applied this joint clustering-and-tracking framework to two sets of channel measurements performed in to completely different scenarios.

The first set of measurements was conducted in an indoor scenario at 2.55 GHz using an Elektrobit Propsound™ CS MIMO channel sounder. We will present results for a measurement route in a students lab. More details on this measurement campaign and a floor plan of the scenario is presented in [14]. The measured impulse responses were post-processed using the ISIS high-resolution algorithm [20] to obtain propagation paths for each snapshot of the channel.

The second set of measurements were conducted in an outdoor scenario in the 300 MHz band using the RUSK Lund MIMO channel sounder. A description of the measurement campaign can be found in [21]. The measured impulse responses were post-processed by a SAGE algorithm to obtain propagation paths for each snapshot of the channel.

[1]Note that the principal-value calculation rules apply for the angular dimensions

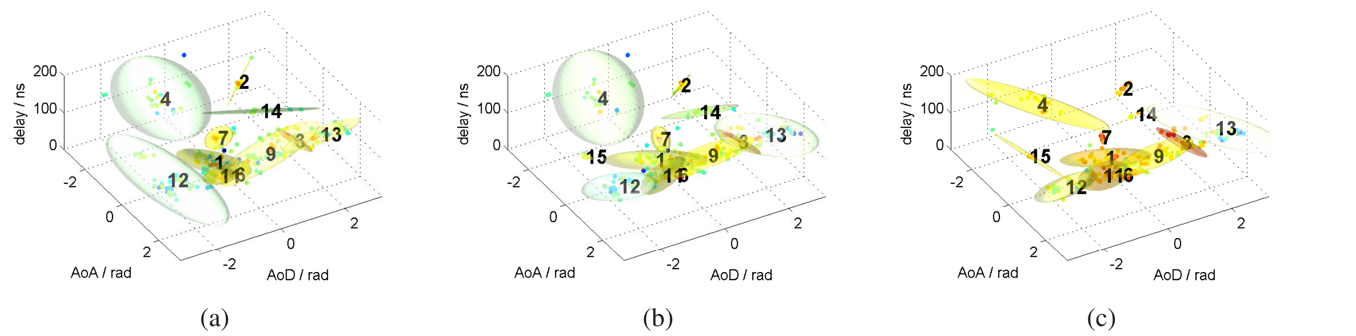

Fig. 2. Tracked clusters from indoor scenario; (a)-(c) show the clusters' evolution over time

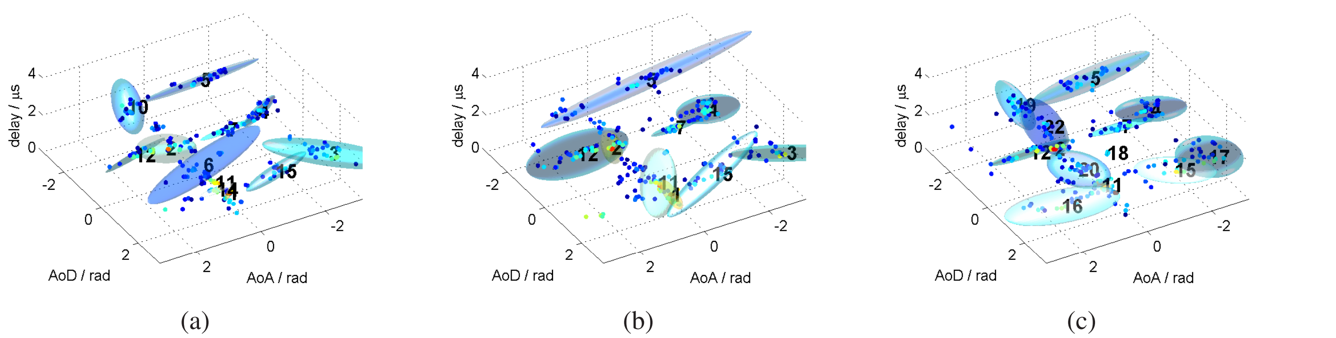

Fig. 3. Tracked clusters from outdoor scenario; (a)-(c) show the clusters' evolution over time

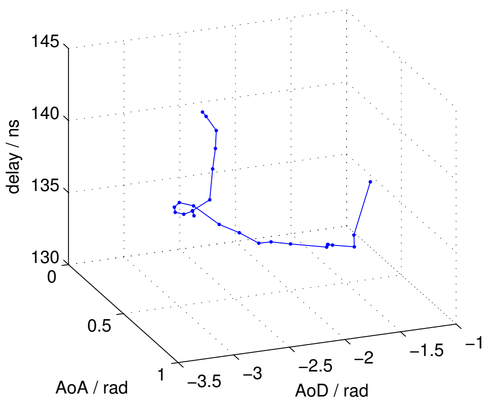

Fig. 4. Tracked centroid of exemplary moving cluster

We applied our joint clustering-and-tracking framework to both sets of measurements and found that the algorithm provides clusters that well-match the time-varying physical propagation mechanisms observed in the measured scenarios. Exemplary plots from both measurements are shown in Figures 2 and 3. The individual plots show the evolution over time. Propagation paths are marked by dots, their power is colour coded from red (strong power) to blue (weak power). Clusters are shown by ellipsoids (capturing 99.9% of the power of the included paths), where the colour describes the mean power of the included paths, and the numbers indicate the cluster IDs placed at the cluster centroid.

In the indoor scenario in Figure 2 we observe up to 14 clusters, which can be well tracked over time. Cluster 3 shows strongest power, but many other clusters show rather high power, too. Cluster 2 is very narrow indicating a strong reflection with larger delay. When following cluster 14 over time, one can see that it vanishes slowly. The same holds true for cluster 15. Also note the movement of both clusters 12 and 13 toward larger AoDs.

The trajectory of the centroid of one exemplary strongly moving clusters is provided in Figure 4. The cluster is rapidly moving toward increasing AoD and smaller delay, while it shows only slow movement in the AoA.

In total, 218 clusters were tracked in 393 snapshots, where 59 clusters existed for just one snapshot and could not be tracked. A histogram of the (logarithmic) lifetimes of the other 159 clusters is provided in Figure 5. This histogram does not indicate a good fit to any analytical distribution.

The outdoor scenario in Figure 3 shows few very distinct small cluster with high powers (clusters 1 and 2) and a large number of clusters with very low power. The strong clusters stem from the LOS path and a strong specular reflection, whereas the weak clusters are due to scattering on trees and rough surfaces. Also in this scenario the clusters can be tracked very well.

In this scenario, 169 clusters were tracked in 197 snapshots, where 132 clusters existed for more than one snapshot. The histogram in Figure 6 would indicate an exponential distribu-

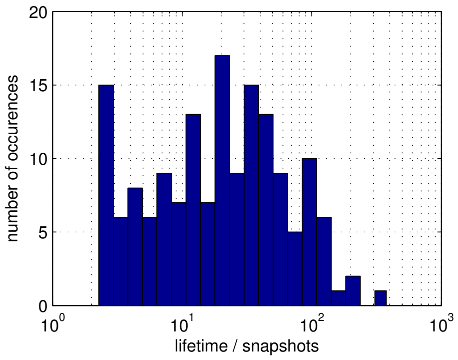

Fig. 5. Histogram of cluster lifetimes (snapshots) in indoor scenario

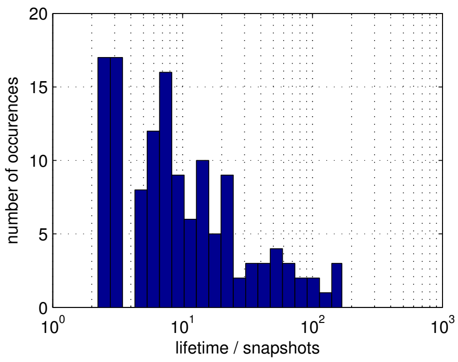

Fig. 6. Histogram of cluster lifetimes (snapshots) in outdoor scenario

tion of the cluster lifetimes.

V. CONCLUSIONS

This paper presented a novel joint clustering-and-tracking algorithm in order to identify time-variant cluster parameters for geometry-based stochastic MIMO channel models.

Using a Kalman filter to track the clusters and to predict the cluster position for the next time instant significantly improves the ability to track clusters.

For tracking multiple clusters, we introduced a novel method for cluster association of predicted and identified clusters. By using the cluster spreads we could improve the cluster association considerably.

Applying the framework on two highly different types of MIMO channel measurements led to consistent results. The combination of tracking and clustering allows to identify the time-variant properties of clusters coherently.

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