Improved Multipath Clustering of a Small Urban Macrocellular MIMO Environment at 4.5 GHz

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1. Introduction

Multipath clustering has been started to be considered in Multiple-Input Multiple-Output (MIMO) propagation channel models [1]. Availing the benefits of MIMO systems also includes knowing how these multipath clusters behave in order also to come up with better MIMO wireless system designs. Assuming the presence multipath clusters in a certain channel scenario, the knowledge of them includes identifying them in a satisfactorily accurate way. Cluster identification was done manually in most of previous studies, e.g. [2], thus affecting their subsequent channel models. However, as large data sets from channel sounding have made the manual identification of clusters cumbersome, the use of clustering algorithms has been a resort. Thus, clusters can be identified objectively and eventually modeled without visual bias. In this paper, using an optimized automatic clustering approach, results of the determination of the clustering of multipaths are presented. Our observations show that the distribution of cluster power proportion should also be taken into account when modeling clusters as unnecessary exclusion of least clusters may not represent the characteristics of clusters in the channel.

2. Estimated MIMO Propagation Channel Data

Using a maximum likelihood multidimensional parameter estimation algorithm [3], path parameters such as the time delay, direction of departure and arrival, and complex polarimetric path weights were extracted. Here we denote our n^{th} path channel data as $\mathbf{X}_n = [\tau_n \quad \phi_n^{\text{BS}} \quad \theta_n^{\text{BS}} \quad \phi_n^{\text{MS}} \quad \theta_n^{\text{MS}}]$, where τ is the delay of the signal, with azimuth (ϕ) and co-elevation (θ) angle of departure from the base station (BS) to the mobile station (MS). The estimation algorithm is based on the double-directional channel concept, which makes the results independent of the antennas used. Pertinent channel sounder and environment details are in Table 1(a) and Table 1(b), respectively. A continuous twenty snapshot frame was chosen for clustering, in which the clustering was done per snapshot. These snapshots were taken after midnight while the channel sounder was being moved at a speed of about 0.14 m/s in a street with no moving cars. In the post processing, strongest paths that represent the LoS were removed and only those signals down until -90 dB were included. $\mathbf{X}$ is then inputted to the clustering algorithm, together with the number of clusters, K, which was adjusted from 2 to 14.

3. Clustering Approach

3. 1 K-means Algorithm & Global Optimization Using Simulated Annealing

Without consistent reproducibility, visual cluster identification methods can become unwieldy and subjective when applied to large data from channel sounding. So we resorted to the use of clustering algorithms. We used the K-means algorithm for clustering. Its criterion is: $\min_{\{\mathcal{C}_k\}_{k=1}^{K}} \left[\sum_{k=1}^{K} \sum_{\mathbf{X} \in \mathcal{C}_k} d(\mathbf{X}, \boldsymbol{\mu}_k)\right]$, where $d(\cdot)$ is the multipath-distance measure, and $\boldsymbol{\mu}_k$ is the

Table 1: Measurement system and environment details

(a) Medav-RUSK-Fujitsu MIMO channel sounder

Carrier frequency	4.5 GHz
Bandwidth	120 MHz
BS antenna	Uniform rectangular array
	V & H pol. 4×2 patches
MS antenna	Stacked uniform circ. array
	V & H pol. 24×2 patches
Tx signal	Wideband multitone
Maximum τ	3.2 μs

(b) Small urban macrocell scenario

BS height	~85 m
MS height	~1.80 m
BS-MS distance	~320 m
Structure type	residential & industrial
Sounding area	Kawasaki, Kanagawa, Japan

cluster centroid of the cluster $\mathcal{C}_k$. We used the multipath component distance for $d(\cdot)$ [4], which is basically a normalized Euclidean distance measure for multipath parameters. Clustering was performed until convergence over all the dimensions of $\mathbf{X}$ simultaneously. The K-means clustering algorithm is a locally optimized way of solving a combinatorial minimization problem of identifying clusters, which is a nondeterministic polynomial-time hard (NP-hard) problem. Thus K-means is only able to guarantee locally optimal results. Using simulated annealing, we tried to circumvent this local minima feature. Simulated annealing is a stochastic optimization strategy that is conceptually a Monte Carlo method modeled according to physical annealing from statistical mechanics [5].

3.2 Number of Clusters (K)

Determining the best K is difficult because it also requires *a priori* knowledge of the formation of clusters in the environment, which is not practically available. Nonetheless, the best K could be found by evaluating the clustering results using clustering validation indices. A clustering validation index tells us about the quality of clustering results that could give the best grouping. We used the global silhouette index, Davies-Bouldin index, the Calinski-Harabasz index, the Kim-Parks index, and a dynamic index. The silhouette index, s_{nk}, could measure how similar a multipath is to all multipaths in its own cluster k compared to all multipaths of the cluster nearest to it. It is expressed as, $s_{nk} = (b_{nk} - a_{nk})/\arg\max\{b_{nk}, a_{nk}\}$, where $a_{nk} = \frac{1}{|\mathcal{C}_k|}\sum_{\mathbf{X}\in\mathcal{C}_k} d(\mathbf{X}_n, \mathbf{X}_m)$, $(m \neq n)$; while $b_{nk} = \arg\min\limits_{j \neq k}\left\{\frac{1}{|\mathcal{C}_j|}\sum_{\mathbf{X}_m\in\mathcal{C}_j} d(\mathbf{X}_{nk}, \mathbf{X}_{mj})\right\}$. The best K could be found as $K_{\mathrm{SI}} = \arg\max\limits_{K}\left\{\frac{1}{K}\sum_k\left(\frac{1}{|\mathcal{C}_k|}\sum_{n\in\mathcal{C}_k} s_{nk}\right)\right\}$. The Davies-Bouldin index is a function of the ratio of the intra-cluster separation sum (S_i) to the inter-cluster separation. The best K is found as, $K_{\mathrm{DB}} = \arg\min\limits_{K}\left\{\frac{1}{K}\sum_k\left(\arg\max\limits_{j\neq k}\left\{\frac{S_k+S_j}{d(\boldsymbol{\mu}_k,\boldsymbol{\mu}_j)}\right\}\right)\right\}$ where $S_i = \frac{1}{|\mathcal{C}_i|}\sum_{n\in\mathcal{C}_i} d(\mathbf{X}_n, \boldsymbol{\mu}_i)$. As for the Calinski-Harabasz index, it is a ratio of the trace of the between-cluster scatter matrix, $\mathbf{B} = \sum_k |\mathcal{C}_k|\, d(\boldsymbol{\mu}_k, \boldsymbol{\mu})\, d^{\mathrm{T}}(\boldsymbol{\mu}_k, \boldsymbol{\mu})$, to the trace of the within-cluster scatter matrix, $\mathbf{W} = \sum_k\sum_{n\in\mathcal{C}_k} d(\mathbf{X}_n, \boldsymbol{\mu}_k)\, d^{\mathrm{T}}(\mathbf{X}_n, \boldsymbol{\mu}_k)$, where $\boldsymbol{\mu}$ is the global centroid. The best K is expressed as $K_{\mathrm{CH}} = \arg\max\limits_{K}\left\{\frac{\mathrm{Trace}(\mathbf{B})/(K-1)}{\mathrm{Trace}(\mathbf{W})/(N-K)}\right\}$. The Kim-Parks index is a function of the sum of the total intra-cluster separation and the minimum distance between cluster centroids. Using it, the best K is $K_{\mathrm{KP}} = \arg\min\limits_{K}\left\{\left(\frac{1}{K}\sum_k S_k\right) + \frac{K}{\arg\min\limits_{j\neq k}\left\{d(\boldsymbol{\mu}_k,\boldsymbol{\mu}_j)\right\}}\right\}$, where each summand of the argument is normalized as, $x_{\mathrm{arg}} = (x - x_{\mathrm{min}})/(x_{\mathrm{max}} - x_{\mathrm{min}})$. For the dynamic index considered, it tries to include the geometrical aspect of $\mathbf{X}$ while taking account of the affinity of each cluster. It determines the best K as $K_{\mathrm{DI}} = \arg\min\limits_{K}\left\{\frac{\arg\max\left\{d(\boldsymbol{\mu}_k,\boldsymbol{\mu}_j)\right\}}{\arg\min\limits_{j\neq k}\left\{d(\boldsymbol{\mu}_k,\boldsymbol{\mu}_j)\right\}} + \frac{\alpha}{K}\frac{\sum_n\sum_k \mathrm{var}(\mathbf{X}_n\in\mathcal{C}_k)}{\sum_n \mathrm{var}(\mathbf{X}_n)}\right\}$ where $\alpha = \frac{\arg\max\{d(\mathbf{X}_n,\mathbf{X}_m)\}}{\arg\min\limits_{n\neq m}\{d(\mathbf{X}_n,\mathbf{X}_m)\}}\cdot\frac{\sum_n \mathrm{var}(\mathbf{X}_n)}{\sum_n\sum_{k=1}^{2}\mathrm{var}(\mathbf{X}_n\in\mathcal{C}_k)}$ while $\mathrm{var}(\cdot)$ denotes the variance.

Table 2: Example $\nu(K)$ for $K = 2$ to $K = 5$ and average rank aggregation

K	ν_{SI}	ν_{DB}	ν_{CH}	ν_{KP}	ν_{DI}	$\mathrm{sr}_{\mathrm{SI}}$	$\mathrm{sr}_{\mathrm{DB}}$	$\mathrm{sr}_{\mathrm{CH}}$	$\mathrm{sr}_{\mathrm{KP}}$	$\mathrm{sr}_{\mathrm{DI}}$	$\mathrm{sr}\left(\overline{\forall \mathrm{sr}}\right)$
2	0.572	0.705	84.281	0	36.365	3	3	2	4	2	3
3	0.587	0.561	114.321	0.245	31.087	4	4	4	3	4	4
4	0.446	0.731	92.7	1.044	35.525	2	2	3	2	3	2
5	0.318	0.865	74.684	2	39.494	1	1	1	1	1	1

3. 3 Average Rank Aggregation

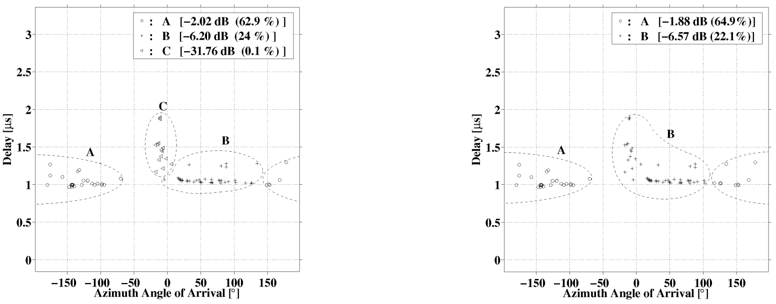
Given a certain K, each argument in K_{SI}, K_{DB}, K_{CH}, K_{KP}, and K_{DI}—denoted here by $\nu(K)$—has a different scale from one another, an example of which is in Table 2. Since these $\nu(K)$s differ in evaluating the qualities of the clustering results, it is also not straightforward to normalize them to one scale. To address these issues and to not only depend on one clustering validation result, we adopted the weighted voting aggregation of [6] but with our proposed modification: instead of scoring $\nu(K)$ by assigning weighted votes to each of them, we score them by their statistical rank—$\mathrm{sr}(\nu)$. This improves the determination of the best K as it does not depend on weights. This strategy is shown in the same table using the $\nu(K)$ example, where the result points that the best K is 3 based on the highest $\mathrm{sr}(\cdot)$ of the $\mathrm{sr}(\nu)$ average of all clustering validation indices.

4. MIMO Clustering Results

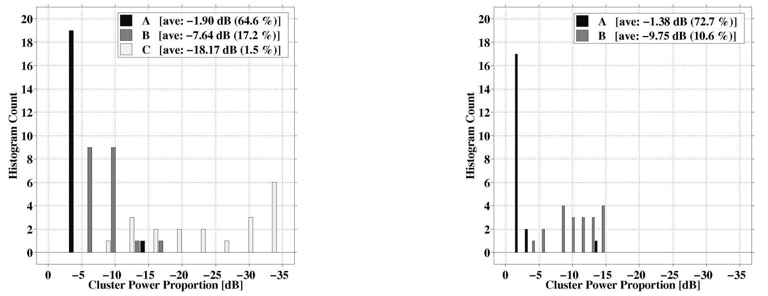
We show our results in terms of the cluster power proportion—ratio of the cluster multipath power to the received power, which includes the dense multipath components. Our results open up concerns in coming up with the best multipath clustering as cluster significance plays a role to whether a cluster should be considered or not. Cluster significance is critical since it may positively or negatively impact the resulting cluster model. For example, if we have, say 100 multipaths that each has a -30 dB power, discarding them is tantamount to filtering -10 dB from the received power. Items that goes in delimiting cluster significance not only includes the power but spread thresholds as well, as it would determine the shape and characteristics of clusters. Add to this the number of clusters, which must be considered carefully, as we would see next. In Fig. 1(a), cluster C is the least cluster and seems to be negligible. It was grouped to the nearest cluster for the $K = 2$ result in Fig. 1(b). However, neglecting it and just using the $K = 2$ result may not be helpful when we see the distribution of the cluster power proportion. Taking all the snapshots considered, the average K of the route is 3. We show its cluster power proportion histogram in Fig. 1(c) and that of $K = 2$ in Fig. 1(d). It could be more observed in those histograms that the distribution of cluster power should also be taken into account as clusters are modeled because unnecessarily cutting them off, or removing least clusters may not give an accurate picture of the channel. As could be seen, cluster C in Fig. 1(c) (which represent least clusters), though small in power proportion, more of it occurs at the far right end of the scale. These least clusters are increasing as the power proportion level decrease. So even though cluster C is least, its contribution increases, given that it is within the threshold suggested in [1]. Thus, the clusters in Fig. 1(c) portrays a better picture of multipath clustering than that of Fig. 1(d), in which the significance of cluster C is effectively distributed to the two clusters. Therefore, if the clustering results of Fig. 1(d) were taken, the subsequent model would not be able to capture the characteristics of the other cluster and could result to unfaithful reconstruction of clusters in the propagation channel.

5. Conclusion

We presented an optimized way of clustering where we used simulated annealing with K-means algorithm in order to escape local minima. Included in the clustering approach is the average rank aggregation strategy, which was proposed and used to improve the determination



(a) $K = 3$ (b) $K = 2$



(c) Entire route; $K = 3$ (d) Entire route; $K = 2$

Figure 1: Results considering the cluster power and K

of K. Applying the approach to a small urban macrocell channel data measured at 4.5 GHz and considering the distribution of the cluster power proportion, least clusters should not unnecessarily be neglected in considering their significance so as to be able to have a satisfactorily accurate characterization of the channel.

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