2nd URSI AT-RASC, Gran Canaria, 28 May – 1 June 2018

A Tracking-Based Multipath Components Clustering Algorithm

Qingbi Zheng(1), Ruisi He(2), and Chen Huang(3)
(1) School of Electronic and Information Engineering, Beijing Jiaotong University, Beijing, 100044, China, 17120179@bjtu.edu.cn
(2) State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University,Beijing, 100044, China, ruisi.he@bjtu.edu.cn
(3) School of Computer and Information Technology, Beijing Jiaotong University, Beijing, 100044, China, morning@bjtu.edu.cn

Abstract

Wireless channels are generally considered to be time-variant. Hence how to build an effective clustering algorithm in time-variant channels is still one of the current research topics. In this paper, the tracking algorithm based on a total probability maximization estimation and the KPowerMeans clustering algorithm are applied for the clusters in the time-variant radio propagation channel. The algorithm is validated by simulating dynamic channels, and the simulation results show a good performance of the proposed algorithm.

1 Introduction

Channel modeling has been one of the most significant research topics in wireless communication, because any actual systemąŕs performance depends on the channel. The main purpose of channel modeling is to describe the MPCs under different environments while considering the accuracy and complexity of the model. Using the accurate channel models to analyze and evaluate the system greatly improves the efficiency of the work. And we can adjust the parameters of the channel model or modify the structure of the model to meet the characteristics of the different actual channels.

A large number of actual measurement results show that the multipath component is distributed in the form of clustering in the actual environment. In recent years, the cluster based channel model has been widely used in the standardized channel model. A cluster in a channel is a set of paths with similar attributes or parameters, including azimuth-of-arrival (AoA), azimuth-of-departure (AoD), Delay, and power [1].

Generally speaking the radio channels are usually time-variant. In the process of signal propagation, there will be the path fading caused by the propagation distance, the shadow fading caused by obstacles, the doppler effect caused by the relative motion between the transmitter and the receiver, and the delay expansion caused by the different arrival time to the receiver of MPCs. These factors make wireless channels gradually evolve into time variant channels affected by time and frequency.

The time variation of radio channels has a great impact on the characterization of dynamic channels. This variability should be considered during channel modeling. Therefore, the dynamic MPC clustering algorithm is needed for modeling time-varying channels. Because of the complexity of time-variant channels, there is still lack of general methods for radio channel multipath clustering. Automatic clustering algorithms to identify MPC clusters are still insufficient. In the past, the clustering phenomenon of MPCs is often analyzed by visual inspection. However, the accuracy of this method is very low, and it is not suitable for large amounts of data from dynamic channels.

Clustering analysis in machine learning has been widely used. People can use clustering to better identify the structure of the data, understand the global distribution, and then find the relationship among the various attributes of the data. After the application of the clustering algorithms in machine learning to automatic identification of clusters in wireless channels, there are several different directions of this problem. But the basic algorithms are K-means, density-based spatial clustering of applications with noise (DBSCAN), wave-cluster, etc.

Therefore, existing clustering methods can be divided into two categories. One uses the power and time delay of the MPCs as the main basis for cluster identification to cluster the multipath components, such as [2–5]. The other uses the angle domain data (AoA and AoD) and delay to cluster the MPCs, such as [6, 7].

In [2], an automatic clustering algorithm based on power and delay properties is proposed. The algorithm uses the least square method for linear fitting, and draws power delay profile (PDP). The relationship between the two is linearly attenuated. The MPCs in the same cluster have the same or similar linear relationship with the PDP. The algorithm compares non line of sight (NLoS) and line of sight (LoS) paths with good clustering results. However, the clustering effect of this algorithm is greatly influenced by the judgment value of the fitting degree. Choosing inappropriate values will make clusters fragmented or even identify many clusters into one cluster.

The idea of [3,4] is similar. It also uses PDP to cluster. The core idea of [3] is to detect at the beginning of the nonzero response. The threshold of delay interval is set. If the delay between two power responses is smaller than the threshold, the two MPCs will be zoned to one cluster, otherwise, it will be rowed into different clusters. After the initial clustering, the deviation threshold is set to further cluster, whereas the effect of the algorithm is similar to that of [2].

In [4], the kurtosis measurement is added to determine the shape difference of PDP. In addition, the regional competition algorithm used in the field of computer vision is adopted to extract the nonlinear and linear distribution characteristics simultaneously. The algorithm has high compatibility with MPCs and isn't affected by the channel state.

Considering the information of angle domain and delay of MPCs, [6] presents a method of clustering by using an ordered cluster algorithm in the domain of machine learning. However, the clustering effect of this algorithm is not good, and later it needs manual observation to cluster MPCs.

The study in [7] introduces a concept of Multi-path Component Distance (MCD) to measure the distance between MPCs, and uses hierarchical tree method to cluster. The simulation experiment is carried out under the SCM channel model. Under different cluster angle extensions, it compares the effect of different distance indicators on the cluster identification. It is verified that MCD can significantly improve the precision of clustering.

MCD is combined with the classical algorithm K-means algorithm in clustering analysis to achieve better clustering performance in [8]. It is proposed that when the AoA, AoD and delay attributes of the MPCs are considered, the clustering effect of the algorithm is better, and the result will be more accurate.

In view of this kind of clustering idea, [9] made further improvement and proposed the KPowerMeans clustering algorithm. Based on the K-means algorithm, it adds the power attributes of MPCs as a weighting factor. The higher power of the MPC, the greater its impact, which indicates that the power weighting has practical significance. Under the influence of power, the cluster centroid will gradually close to the high-power MPCs in the iterative process of the algorithm, which makes the performance of the cluster more excellent. However, this research cannot overcome the limitations of K-means algorithm itself. It depends on parameter settings in initial steps which makes clustering results uncertain and does not necessarily obtain optimal clustering results. Moreover, it has poor performance in N-LoS channel environment.

After that, there are many literatures improving KPowerMeans clustering algorithm. Aiming at the problem that the KPowerMeans algorithm relies too much on initializing the cluster centroids and the clustering is inefficient, [10] proposed using the most powerful MPCs as initialized cluster centroids. This method effectively improves the performance of the KPowerMeans clustering algorithm. [11] suggests that the clustering method of KPowerMeans clustering algorithm is not completely applicable for MPCs in real environment. The more complex the channel scenario is, the worse performance of the algorithm it will be.

These algorithms have some limitations. The clustering accuracy in dynamic time-variant channels is low, and some of them are not suitable for dynamic time-variant channels.

In the process of clustering analysis in dynamic time-variant channels, the characteristics of time-variant channels need to be counted and tracked. Therefore, a novel framework of tracking and clustering is proposed, where KPowerMeans is firstly used for clustering MPCs and then heuristic method is used for transaction. The algorithm is validated in a simulation channel.

2 Framework

In order to cluster the MPCs in the dynamic time-variant channels, the proposed algorithm is divided into two steps: i) identify MPCs' trajectories, and ii) cluster MPCs on the basis of the MPC moving trajectories. In the first stage, the probability of all moving trajectories is first counted. After that, the total probability of all trajectories is calculated, and the probability tracking method is used to maximize the total probability. Record the trajectory corresponding to the maximum total probability. Here the trajectories refer to the moving paths of MPCs in successive snapshots, and one trajectory connects two same MPCs in successive snapshots. The second stage uses the KPowerMeans clustering algorithm [8, 9]. In the previous work of [12], the method of tracking probability estimate value is introduced briefly.

Since there is generally more than one MPC in consecutive snapshots, there are many possible trajectories in two adjacent snapshots, whereas the true trajectory is only one. The primary goal of the first step is to identify the true trajectories of MPCs in every two successive snapshots. It is found that MPCs usually have random motions, [13] although the direction of each MPC can't be significantly changed in a short time. Therefore, each MPC has a corresponding different trajectory moving probability. Then trajectory is weighted by a moving probability to identify trajectories accurately. The true trajectories are obtained by maximizing the total probabilities of all selected trajectories.

Then, the KPowerMeans algorithm is used to cluster the MPCs based on the trajectories. The flowchart of the proposed algorithm is shown in Figure 1. A range K for the possible number of clusters has to be specified initially, then the algorithm assigns each MPC to a cluster and estimates the correct number of clusters. Here, the Xie-Beni [14] validation method is used. The number of clusters, K, and the data from all MPCs, P and X, are external parameters for the clustering algorithm. For each possible K, the clustering algorithm KPowerMeans is performed, and the results are gathered in the data sets RK. Subsequently, each result is validated by validation method.

Determining the number of possible clusters, we select the starting position of the centroids from the data X randomly. Set the maximum number of iterations, which is represented by i, and the iteration begins with the i=1. Take the product of the power of the MPCs with the distance (MCD) of the MPCs and the cluster centroids as the selected parameter. By minimizing the parameter, the MPCs are assigned to the cluster centroids. Meanwhile the index k is preserved. The location of the cluster centroids are then recalculated according to the MPCs contained in each cluster. Repeat this iterative process until the cluster centroids are no longer moving, or the number of iterations reaches the maximum value set. The output of the algorithm is the index set and the associated cluster centroids obtained by the last iteration.

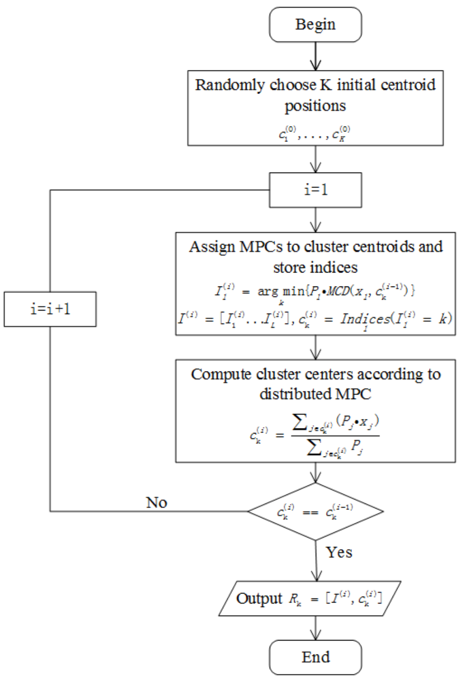

Figure 1. KPowerMeans algorithm.

3 Simulation results

In this paper, we validate the tracking algorithm by using random generated MPCs. We use different statistical distributions for AoA, AoD, delay and power based on a measurement-based dynamic channel model in [13]. More details of dynamic simulation can be found in [13] and, all

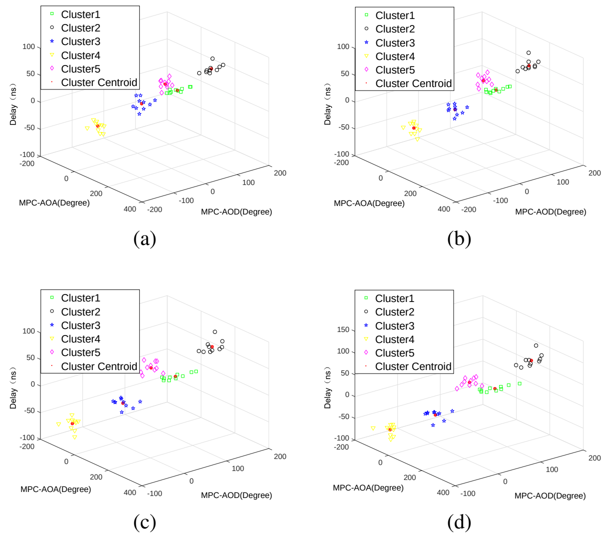

Figure 2. Performance of the clustering algorithm for the time-variant channel in snapshots 1, 2, 3, and 4. (a)-(d) Clustering results for the channel with five clusters and ten MPCs in each cluster.

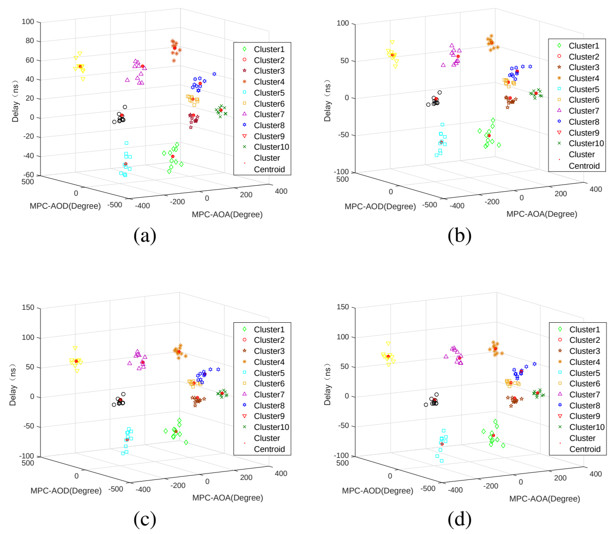

Figure 3. Performance of the clustering algorithm for the time-variant channel in snapshots 1, 2, 3, and 4. (a)-(d) Clustering results for the channel with ten clusters and ten MPCs in each cluster.

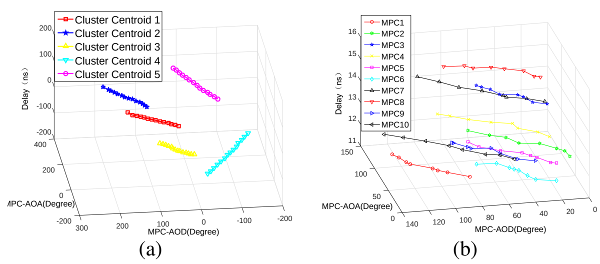

Figure 4. Moving trajectory. (a) Moving paths of MPCs in a cluster. (b) Moving paths of cluster centroids.

the parameters of distributions used in this paper are estimated using a nonlinear least-square regression method. In the dynamic simulation model, lifetime is a time window, which describes the time duration from MPC appearance to disappearance. All the variations of MPC happen during its lifetime. It is found that MPC lifetime is independent of the mean values of MPC delay and azimuth [13].

In this paper, the proposed algorithm is validated by using randomly generated MPCs with a fixed number of ten. Simulation validation is done in the urban channel model in [13]. Figures 2 (a)-(d) show the results of clustering algorithm for the channel with five clusters and ten MPCs in each cluster, where four successive snapshots are considered. Figures 3 (a)-(d) show the results of clustering algorithm for the channel with ten clusters and ten MPCs in each cluster, where four successive snapshots are considered. We mark different clusters with different colors and different shapes and cluster centroids with red circles. As we can see, the proposed algorithm can recognize clusters correctly. Different clusters have different moving tracks. When the number of clusters is large, the performance is also relatively good. In Figure 4 (a), the channel has eight snapshots and each snapshot includes one cluster with ten MPCs. The moving paths of MPCs are plotted by linking the MPCs in different snapshots. Figure 4 (b) shows the moving paths of cluster centroids.

4 Conclusion

In this paper, a novel framework of clustering and tracking algorithm is proposed to solve the clustering problem in time-variant channels. The tracking problem is solved by maximizing the total probability of the movements and the MPCs in time-variant channels are clustered based on the moving probability and KPowerMeans algorithm. The algorithm is verified by a dynamic simulation model and the results show that the algorithm has a good performance.

References

[1] R. He, Q. Li, B. Ai, Y. L. Geng, A. F. Molisch, V. Kristem, Z. Zhong and J. Yu, "An automatic clustering algorithm for multipath components based on Kernel-power-density," in *Proc. IEEE WCNC*, 2017, San Francisco, USA, Mar 19-22, 2017, pp. 1-6.

[2] J. Chuang, S. Bashir, D. G. Michelson, "Automated Identification of Clusters in UWB Channel Impulse Responses," in *Proc. IEEE CCECE*, Vancouver, BC, Canada, Apr 22-26, 2007, pp. 761-764.

[3] M. Corrigan, A. Walton, W. Niu, J. Li, T. Talty, "Automatic UWB clusters identification," in *Proc. IEEE RWS*, 2009, San Diego, CA, USA, Jan 18-22, 2009, pp. 376-379.

[4] C. Gentile, "Using the Kurtosis measure to identify clusters in wireless channel impulse responses," *IEEE Trans. Antennas Propag.*, vol. 61, no. 6, pp. 3392-2295, Mar. 2013.

[5] D. Shutin, G. Kubin, "Cluster analysis of wireless channel impulse responses with hidden Markov models" in *Proc. IEEE ICASSP*, Montreal, Que, Canada, May 17-21, 2004, pp. 124-127.

[6] J. Salo, J. Salmi, N. Czink, and P. Vainikainen, "Automatic clustering of nonstationary MIMO channel parameter estimates," in *Proc. Inform. Commun. Technol.*, Cape Town, South Africa, May 2005, pp. 1ÍC5.

[7] N. Czink, P. Cera, J. Salo, E. Bonek, J. P. Nuutinen, and J. Ylitalo, "Automatic clustering of MIMO channel parameters using the multipath component distance measure," in *Proc. IEEE WPMC*, Aalborg, Denmark, Sept, 2005. pp 3-7.

[8] N. Czink, P. Cera, J. Salo, E. Bonek, J.P. Nuutinen, and J. Ylitalo, "Improving clustering performance using multipath component distance," *Electron. Lett.*, vol. 42, no. 1, pp. 33-35, 2006.

[9] 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 *Proc. IEEE VTC*, Montreal, Que, Canada, Sept 25-28, 2006, pp. 1-5.

[10] S. Mota, F. Perez-Fontan, A. Rocha, "Estimation of the number of clusters in multipath radio channel data sets," in *Proc. IEEE EUCAP*, Rome, Italy, April 11-15, 2011, pp. 3232-3236. . IEEE Transactions on Antennas and Propagation, 2013, 61(5): 2879-2883.

[11] C. Schneider, M. Bauer, M. Narandzic, W. A. Th. Kotterman, R. S. Thoma, "Clustering of MIMO channel parameters-performance comparison," in *Proc. IEEE VTC*, Barcelona, Spain, April 26-29, 2009, pp. 1-5.

[12] C. Huang, R. He, Z. Zhong, Y. L. Geng, Q. Li, and Z. Zhong, "A novel tracking based multipath component clustering algorithm," *IEEE Trans. Antennas Propag.*, vol. 16, no. 1, pp. 2679-2683, Aug. 2017.

[13] R. He, O. Renaudin, V. M. Kolmonen, K. Haneda, Z. Zhong, B. Ai, and Claude. Oestges, "A dynamic wideband directional channel model for vehicleto-vehicle communications," *IEEE Trans. Ind. Electron.*, vol. 62, no. 12, pp. 7870-7882, Dec. 2015.

[14] X.L. Xie and G. Beni, "A Validity Measure for Fuzzy Clustering," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 13, pp. 841-847, 1991.