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A Time-Varying Clustering Algorithm for Channel Modeling of Vehicular MIMO Communications

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Abstract

Currently, the research of channel modeling pays more attention to time-varying channels, e.g., vehicle-to-vehicle (V2V) communications. Meanwhile, it is found from many measurements of wireless channels that the multipath components (MPCs) are usually distributed in groups, which is considered as the clustered MPCs. This paper thus proposes a novel clustering algorithm for the time-varying channels, which clusters the dynamic MPCs by using the evolution patterns over time. Through the evaluation based on the realistic V2V measurement data, the proposed algorithm achieves relatively better performance compared with the conventional methods.

1 Introduction

Channel modeling plays an important role in wireless communication system design. Supported by a large body of channel measurements [1, 2], it is found that the multipath components (MPCs) usually distribute in groups in wireless channels. Such that, considering the trade-off between the computation complexity and the accuracy of channel models, most of the current research models wireless channel based on the structure of the MPCs' cluster, e.g., COST 2100 [3], 3GPP Spatial Channel Model [4], and WINNER [5]. Parameterization of the models from measurements requires estimation of the MPCs' parameters, and subsequent clustering of MPCs.

Generally, most channel measurements in the past are conducted to collect channel impulse response or transfer function in typical channel scenarios, e.g., urban, suburban, or tunnel. The MPCs are extracted by using some high-revolution-parameter-estimation (HRPE) algorithms, e.g., the space-alternating generalized expectation-maximization (SAGE) [6] or RiMax [7]. Next, during the clustering process for channel modeling, the MPCs that show similar characteristics, i.e., delay, power, angle of arrival (AOA), and angle of departure (AOD), are considered as one cluster. In this case, the clustering approaches for the MPCs in each snapshot, namely 'static clustering', have been widely studied in the past, e.g., [8] proposes a kernel-power-density-based algorithm, which exploits the distribution density of the MPCs in the current snapshot, and [9] proposes a power weighted clustering algorithm based on the K-Means method.

Meanwhile, more and more research pays attention to the time-varying wireless channels instead of the static channels, e.g., the vehicle-to-vehicle (V2V) communication channels [10, 11, 12] and the unmanned aerial vehicle (UAV) communication channels [13]. To evaluate and analyze the time-varying channels, the evolution feature of MPCs/clusters need to be characterized. Such that, the clustering problem changes from the 'static clustering' to 'time-varying clustering', which brings more challenges:

- To do a time-varying clustering, MPCs need to be not only clustered but also tracked over time.
- How to exploit the evolution pattern of MPCs for clustering is another challenging problem.

One of the common ways is to conduct the static clustering for the MPCs in each snapshot, then track the identified clusters over time [14, 15, 16, 17]. In this case, simply conducting the static clustering first and tracking afterward cannot well utilize the evolution pattern of the MPCs. Nevertheless, the evolution feature of the MPCs is actually an important characteristic since this feature correlates to the actual movements or changes of the scatterers [18] in the propagation environments.

Therefore, by exploiting the time-evolution characteristic, this work proposes a dynamic clustering approach that can well recognize the evolution pattern of MPCs during the clustering process. The rest of this paper is organized as follows. Section II describes the problem and the details of the proposed algorithm. Section III presents the evaluation based on the measurement data. Finally, Section IV draws the conclusion.

2 Time-varying Clustering Algorithm

This section first describes the clustering problem for time-varying wireless channels, and then elaborates on the details of the proposed algorithm.

2.1 Problem Description

In any wireless channels, the signal propagates from the transmitter (Tx) to the receiver (Rx) via different paths, giving rise to different MPCs. As mentioned before, the parameters of MPCs in each snapshot can be extracted by using the HRPE methods. The most general channel representation is then the double-directional channel model [19], which represents channel as the sum of MPCs with complex amplitude α, delay τ, AOD ϕ_T, elevation of departure θ_T, AOA ϕ_R, elevation of arrival θ_R, and Doppler Δf[1]. We consider M snapshots of data, $m = 1,2,\cdots,M$, where each snapshot contains a number of N^m MPCs. Thus, the n-th MPC in the m-th snapshot can be represented by the multi-dimensional parameter vector $\mathbf{x}_n^m = [\alpha_n^m, \tau_n^m, \phi_{T,n}^m, \theta_{T,n}^m, \phi_{R,n}^m, \theta_{R,n}^m, \Delta f_n^m], n = 1,2,\cdots,N^m$.

The goal of the algorithm is to identify dynamic clusters in the time-varying channels. Apparently, it requires both tracking and clustering of the MPCs extracted in each snapshot. As mentioned before, utilizing the evolution pattern of the MPCs in the parameter space can improve the accuracy of clustering. Therefore, the proposed algorithm identifies the trajectory of each MPC first, then clusters MPCs based on the identified trajectory.

In this case, the MPCs are clustered considering not only the current parameters but also the time-evolution pattern in the history snapshots as well as the future. Note that, this approach can only serve for the off-line analysis, where all the processes of parameter estimation, tracking and clustering are conducted offline. This allows the method to identify different clusters that may temporally have similar channel characteristics but generally show different propagation characteristics, i.e., different evolution patterns.

2.2 Algorithm Description

2.2.1 Multipath Components Tracking

To analyze the time-evolution characteristic of channels, the MPCs need to be tracked over consecutive snapshots. In the past, most of the MPCs tracking algorithms can be roughly divided into two categories: *threshold-based tracking*, i.e., MPCs are tracked based on a fixed or a dynamic threshold [20]; and *minimum distance-based tracking*, i.e., MPCs are tracked based on the minimum distance among each pair [15, 17]. For time-varying channels, it is usually difficult to select a threshold, whether it is fixed or dynamic, for MPCs tracking due to the fact that channel characteristics change over time. We thus use the minimum distance-based solution here. Specifically, there are two types of minimum distance-based tracking: *local minimum distance-based*, i.e., the MPCs pair having the minimum distance is associated and removed first, then looking for the next MPCs pairs that have the minimum distance [17]; and *global minimum distance-based*, i.e., tracking MPCs by seeking the globally minimum distance of all MPCs pairs. Apparently, the local minimum distance-based method usually leads to a locally optimum result, as shown as $\{D_2, D_3\}$ in Fig. 1, where the MPCs pair of $\mathbf{x}_1^m$ and $\mathbf{x}_2^{m+1}$ has the local minimum distance D_2. However, the global optimum result of Fig. 1 should be $\{D_1, D_4\}$.

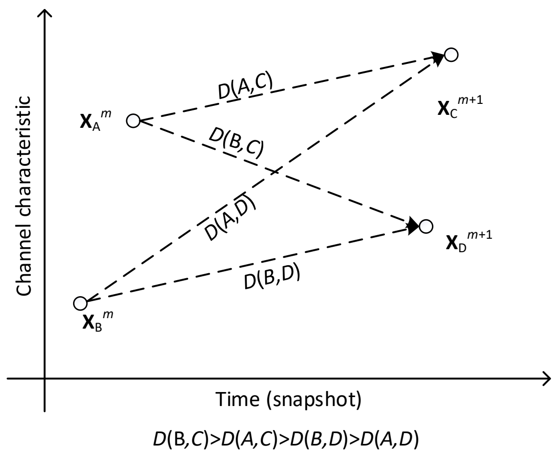

Figure 1. Illustration of different trajectories between the MPCs. $\mathbf{x}_i^m$ and $\mathbf{x}_i^{m+1}$ are the MPCs in m-th snapshot and $m+1$-th snapshot, respectively, whereas D_i is the distance between different MPCs.

To achieve high accuracy of tracking, the MPC tracking method developed in [15] is conducted in this work. As illustrated above, the tracking process between the m-th and the $m+1$ snapshots can be performed by seeking the global minimum distance of all MPCs, which can be expressed as

$$\mathscr{D}_{min}^{m,m+1} = \arg\min_{\mathscr{D}^{m,m+1}} \sum_{\substack{i=1 \\ j=1}}^{N^m} D(\mathbf{x}_i^m, \mathbf{x}_j^{m+1}), \quad i \neq j \tag{1}$$

where $D(\mathbf{x}_i^m, \mathbf{x}_j^{m+1})$ is the distance between the i-th MPC and the j-th MPC in the two consecutive snapshots, and $\mathscr{D}^{m,m+1}$ is the set of all possible trajectories between these snapshots. It is noteworthy that, to compare the differences among different channel characteristics, i.e., delay, power, and angle, we use the normalized Euclidean distance here.

2.2.2 Multipath Components Clustering

As mentioned before, most of the existing clustering methods group the MPCs based on the current channel characteristics, and extend the clustering result into time-domain by using tracking. This paper proposes a novel time-varying

[1] Note that the elevation domain may not be considered in some cases, e.g., the data are collected by using a horizontal uniform linear array.

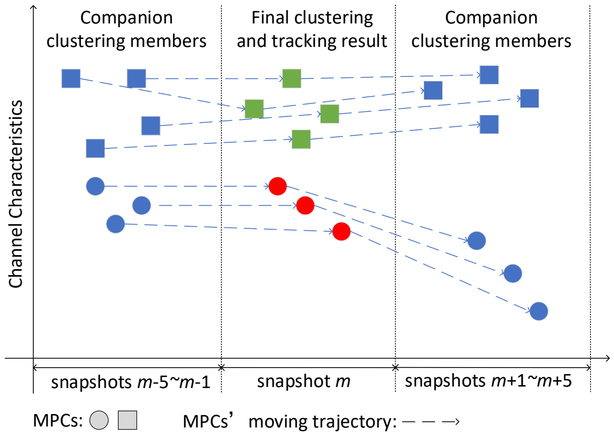

Figure 2. Illustration of the key idea of time-varying clustering.

clustering algorithm that exploits the evolution pattern of the MPCs.

To capture the evolution pattern of the MPCs for clustering, the evolution of the MPCs in the history snapshots and in the future snapshots, which can be obtained since the clustering is processed offline after the tracking, is considered as the clustering objects instead of the individual MPCs. To do so, we define the MPCs in the history and future snapshots as the *companion clustering members*, which are considered during the clustering process but are not account for as the clustering results. Fig. 2 gives the key idea of the proposed method, where the blue squares/dots are the companion clustering members and the red/green squares/dots are the clustering results.

Similar to the tracking process, the normalized Euclidean distance is used to measure the difference between the different evolution patterns. Let $\mathbf{D}_{l_i}$ denote the l_i-th trajectory obtained by the tracking process, which is plotted as the dashed line in Fig. 2. It is noteworthy that, to avoid the impact of evolution pattern in history which is far away to the present, we define a sliding window ΔT, only the evolution trajectories within the sliding window will be considered for the clustering. Such that, assuming two MPCs $\mathbf{x}_a$ and $\mathbf{x}_b$ belong to two trajectories $\mathbf{D}_{l_a}$ and $\mathbf{D}_{l_b}$, and the difference between the evolution pattern of these two MPCs can be expressed as

$$D(\mathbf{x}_a, \mathbf{x}_b) = \sum_{t_i \in \Delta T, \mathbf{x}_a \in \mathbf{D}_{l_a}, \mathbf{x}_b \in \mathbf{D}_{l_b}} \mathscr{N}(||\mathbf{x}_{a,t_i} - \mathbf{x}_{b,t_i}||_2), \quad (2)$$

where $\mathscr{N}$ is the normalized function. By using this measure, the differences among all the evolved MPCs can be obtained for further clustering. As for the further clustering stage, we can conduct the conventional static clustering method since the distance $D(\mathbf{x}_a, \mathbf{x}_b)$ already contains the difference of the evolution pattern. In this work, we use the Kernel-power-density clustering method in [8] to cluster the evolved MPCs.

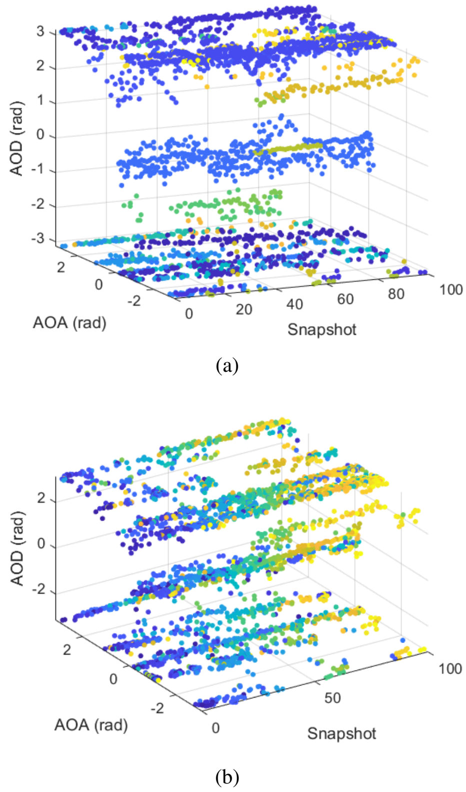

Figure 3. Clustering results of (a) the proposed algorithm and (b) the Kalman-filter-based clustering algorithm.

3 Evaluation

The V2V measurement campaign was conducted with a self-built real-time MIMO channel sounder. The measurements analyzed here were conducted on the campus scenario. The details of the measurement campaign can be found in [21].

To better evaluate the clustering accuracy, we evaluate the proposed algorithm by comparing it with the conventional Kalman-filter-based clustering algorithm. Fig. 3 presents the clustering results of the proposed algorithm and the Kalman-filter-based clustering algorithm, where the different colors represent different cluster IDs. Apparently, the clustering results from the proposed algorithm show more globality of the evolution of MPCs, whereas the Kalman-filter-based clustering algorithm fails to capture the time-evolution characteristics of the MPCs, and thus the cluster-ID is renewed after some snapshots.

4 Conclusion

In this paper, a time-varying clustering algorithm is proposed which exploits the evolution characteristics of the MPCs in the dynamic wireless channels. Evaluating by the channel measurement data, the proposed algorithm is found to have a better performance compared to the conventional Kalman-filter-based clustering algorithm. The results in this paper can be useful for dynamic vehicular channel clustering and modeling.

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