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A Novel Power Weighted Multipath Component Tracking Algorithm

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Abstract

In mobile communications, the wireless channel has been widely considered to be time-variant. To statistically model the time-variant channels, a power weighted dynamic multi-path components (MPCs) tracking algorithm is proposed in this paper, which is based on multiple-target tracking.The problem of seeking potential position is considered as a maximum a posteriori (MAP) estimation in a Markov random process, which can be solved by using the maximum probability. In order to reflect the real condition of channels and improve accuracy of algorithm, statistical behaviors of azimuth, delay, and power of MPCs are generated for algorithm validation by using different distributions according to the dynamic measurements in real-world. Our method is finally validated by using the simulated dynamic channels and is found to have good performance.

1 Introduction

Channel modeling plays an important role in radio communications, since the performance of any practical system depends on channel characteristics. Generally, radio channels are time variant due to movements, which gives rise to significant theoretical challenges in dynamic channel characterizations. Since, most wireless channels can be considered as wide-sense stationary (WSS) [1], in the past, the WSS assumption has been widely used in channel modeling, and is also widely used in the design of wireless communication systems. Nevertheless, the radio channels in real world have been shown to be nonstationary [2], mostly due to the dynamic changes of environments when transmitter and receiver move. In this case, channel characteristics can only be approximated as constant over a finite region in time or space.

Dynamic channel clustering and modeling have received a lot of attentions. However, there lacks automatic clustering algorithm to identify MPC clusters in time-varying channels. In the past, visual inspection was used [3]-[4], which is inapplicable for a large number of MPCs. Some automatic algorithms for radio channel clustering were developed in [5]-[7], however, they are mainly used for static channels. An MPC clustering algorithm, which can be used for dynamic channel clustering is proposed in [8] and [9], where evolutions MPCs are considered. Nevertheless, these algorithms still cannot accurately recognize the cluster in time-varying channels. This is mainly because the dynamic evolution behaviors of MPCs are not fully considered in the existing algorithms.

On the other hand, tracking algorithm design has been an important topic in image processing for tracking crowd [10], pedestrian [11] and headlight [12], which provide many references for MPC tracking algorithm design. The parameters of MPC include angle of departure(AoD), angle of arrival(AoA) and delay, which are similar to positions of targets in group tracking algorithm [12]. Therefore, in order to obtain the statistical characteristic of time varying MPCs, an power weighted MPCs tracking algorithm based on group tracking, which is commonly used in image processing, is proposed in this paper. Furthermore, we establish channel simulator based on a measurement-based dynamic channel model in [13] and validate our algorithm.

2 Multiple Tracking Algorithm for Dynamic MPCs

In time-varying channels, azimuth (e.g., AoD, AoA) and delay are dynamic due to movements. Even if the trajectory of MPC can be identified by visual inspection, an automatic tracking algorithm is needed for channel modeling. To track MPCs, tracking algorithm must successfully recognize the trajectory of MPCs in different snapshots, which means that the algorithm needs to be able to identify the same MPC in different snapshots. In this case, we propose a novel probability based tracking method, where the tracking is conducted by using a maximum a posteriori (MAP) estimation in a Markov random process.

The key idea is to represent the associations of two MPCs from different snapshots within a certain time window. Once a association is done in a time window, we send the results to the next snapshot by sliding the observation window. In this paper, we set the time observation window to be 2 WSS regions to reduce the complexity of algorithm.

Let w be the number of continuous snapshots used for MPC tracking, and they are donated by S_1, S_2,..., S_w. m_w is the number of MPCs in each snapshot, and m_{max} is set to be 90.

MPCs in S_i are donated by $A_1, A_2, ..., A_{m_i}, m_i \in [0, 90]$, and MPCs in S_{i+1} are donated by $B_1, B_2, ..., B_{m_i}$, $m_i \in [0, 90]$. An trajectory t is an ordered pair of MPCs from different snapshots, i.e., $t = (A_{m_a}, B_{m_b})$, meaning that MPC A_{m_a} in snapshot S_i and the MPC B_{m_b} in snapshot S_{i+1} are the same MPC. Let T be the set of all such trajectories, i.e.,

$$\mathbf{T} = \{t_{A,B} = (A_a, B_b) | A_a \in S_i, B_b \in S_{i+1}\} \tag{1}$$

where $A_a = A_1, A_2, ..., A_{m_{\max}}$, $B_b = B_1, B_2, ..., B_{m_{\max}}$.As we mentioned before, MAP estimation is used to obtain the probability of trajectory. Hence, if t exists, the probability of t can be expressed as

$$P(t = (A, B)) = p(A|B)p(B) \tag{2}$$

where $p(B)$ is the probability that MPC B exists in snapshot S_{i+1}, and $p(A|B)$ is the probability that MPC A and MPC B are the same MPC in snapshots S_i and S_{i+1}, respectively. In a Bayesian framework, the posterior probability of hidden variables A is proportional to the product of the likelihood and prior terms,i.e.,

$$p(A|B)p(B) = p(B|A)p(A). \tag{3}$$

Note that, in this case, MPC B is the sample point which has been observed, and tracking algorithm is attempt to find its past position. In other words, $p(B) = 1$, and equation (3) can be rewritten as

$$p(A|B) = p(B|A)p(A) \tag{4}$$

where $p(A)$ represents the probability that A appears in the trajectory. In this way, we can obtain the probability of trajectory in continuous snapshots. In order to avoid the high computational overhead, two continuous snapshots is considered for each implementation. $p(A|B)$ is one potential trajectory, and the main goal of the tracking algorithm is to maximize the probability of all potential trajectory, as shown in equation (5)

$$P^* = arg \max_{p} \sum_{\substack{A \in S_i \\ B \in S_{i+1}}} p(B|A)p(A). \tag{5}$$

From [13] it is found that, MPCs generally have random motions, but the direction of each MPC may not change severely in short time, e.g., within a few WSS time windows. Therefore, the probability of each trajectory can be obtained by comparing distance between MPC A_i and MPC $B_j, i \in S_i, j \in S_{i+1}$. Consider the trajectory of a MPC as a set of (Φ, τ, α), where Φ is the position vector of the tracked MPC, which includes AoA, AoD, and τ and α are the delay and power of the tracked MPC, respectively. An aggregated pairwise probability is used as the measure between two MPCs in continuous snapshots:

$$\sum_{\substack{A \in S_i \\ B \in S_{i+1}}} P_{A,B} = \beta_1 \mathscr{C}(||\Phi_B^{S_{i+1}} - \Phi_A^{S_i}||) + \beta_2 \mathscr{C}(|\tau_B^{S_{i+1}} - \tau_A^{S_i}|) + \beta_3 \mathscr{C}(|\alpha_B^{S_{i+1}} - \alpha_A^{S_i}|) \tag{6}$$

where β_1, β_2, β_3 are weight coefficients of azimuth, delay, and power of the tracked MPCs, and $\alpha_1+\alpha_2+\alpha_3 = 1$. In this case, we use α_1=0.3, α_2=0.3, α_3=0.4 to combine spatial proximity and power characterization into a pairwise probability $P_{A,B}^{S_i,S_{i+1}}$. $\mathscr{C}(\cdot)$ is a probability normalization function, which is developed from the min-max normalization function:

$$\mathscr{C}(x_i) = \frac{x_i - x_{max}}{\sum\limits_{X_i \in S_{i+1}} x_i} \tag{7}$$

To summarize, within each pairwise snapshots, starting from a single MPC, the tracking algorithm cross-scale probabilities of all trajectory to find the most likely track, which is considered to be the true trajectory in reality.

3 Measurement-Based Simulation Model

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 the parameters of distributions used in this paper are estimated using a nonlinear least-square regression method and summarized in Table 1. 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].

If one MPC appearances at observation s' and disappearances at s'' (where $s' < s''$), its lifetime T is given by

$$T = \Delta W \cdot \Delta s = \Delta W \cdot (s'' - s' + 1) \tag{8}$$

where ΔW is the duration of one WSS region. For the sake of analysis, we assume all MPCs have the same lifetime. AoD and AoA is also independent of each other with a similar distribution, which is given by the zero-mean Gaussian distribution [13] as follows

$$f_{2,\phi}(\phi) = \frac{1}{\sigma_\phi \sqrt{2\pi}} \mathtt{exp}(-\frac{\phi^2}{2\sigma_\phi^2}) \tag{9}$$

where σ_ϕ is the standard deviation. As for delay, Gamma distribution is suggested by [13], which is given by

$$f_{2,\tau} = \frac{y^{p_{21}-1} \cdot \mathtt{exp}(-y/p_{22})}{(p_{22}^{p_{21}}) \cdot \Gamma(p_{21})}. \tag{10}$$

It is found in [13] that the normalized MPC power is generally independent of azimuth. There are MPCs with high powers present at nearly all angles. Hence, the power is modeled as a function of excess delay, which is given by a dual-slope model

$$20log_{10}(\alpha) = \begin{cases} q_1 \cdot \tau[ns] & 0 \le \tau < \tau_{a,\mathrm{bp}} \\ q_2 \cdot \tau[ns] + q_3 & \tau_{a,bp} \le \tau \le 700ns \end{cases} \tag{11}$$

Table 1. DYNAMIC MODEL PARAMETERS

Parameter	value	Parameter	value
ΔW[s]	1.15	$k_{\tau,(k_\tau>0)}$	8.09
s_{max}	48	$k_{\tau,(k_\tau<0)}$	-6.94
$\mu\Delta s$	1	$k_{\phi,(k_\phi>0)}$	6.00
$\sigma\Delta s$	13.0	$k_{\phi,(k_\phi<0)}$	-7.54
p_{11}	1.81	$k_{a,(k_a>0,k_\tau>0)}$	0.060
p_{12}	3.05	$k_{a,(k_a<0,k_\tau>0)}$	-0.063
p_{21}	1.48	$k_{a,(k_a>0,k_\tau<0)}$	0.042
p_{22}	9.12	$k_{a,(k_a<0,k_\tau<0)}$	-0.041
$\sigma_\phi(\mathtt{degree})$	76.2	$k_{a,(k_a>0,k_\tau=0)}$	0.049
$\tau_{a,\mathtt{bp}}$[ns]	91.67	$k_{a,(k_a<0,k_\tau=0)}$	-0.004
q_1	-0.19	$\tau_{m,\mathtt{bp}}$[ns]	8
q_2	-0.009		
q_3	-12.93		

where $\tau_{a,\mathtt{bp}}$ denotes breakpoint. In the time varying channel, the variations of azimuth, delay, and power of each MPC within its lifetime need to be modeled. However, the MPCs with short lifetimes are considered to be constant according to [13]. The distinction of short and long lifetimes is expressed as

$$\Delta s = s'' - s' + 1 : \begin{cases} \geq 6, & \mathtt{long\ lifetime} \\ < 6, & \mathtt{short\ lifetime}. \end{cases} \tag{12}$$

For long lifetime MPC, the delay and azimuth are modeled using linear polynomial functions as

$$\tau(t_s) = \tau(t_{s'}) + k_\tau(s' - s'' + 1) \tag{13}$$

$$\phi(t_s) = \phi(t_{s'}) + k_\phi(s' - s'' + 1). \tag{14}$$

$$\alpha(t_s) = \phi(t_{s'}) + k_\phi(s' - s'' + 1). \tag{15}$$

Note that within a particular MPC's lifetime, both k_τ and k_ϕ can be positive, or negative, or 0, with equal probability. Meanwhile, k_α is found to be either positive or negative with equal probability, and the case $k_\alpha = 0$ is rarely observed in measurements.

4 Algorithm Validation

With the dynamic simulation model, we test our MPC tracking algorithm in four different scenarios: i) 5 clusters with only one MPC in each cluster, ii) 5 clusters with three MPCs in each cluster, iii) 5 clusters with seven MPCs in each cluster, and iV) 5 clusters with twenty MPCs in each cluster. The performances of MPC tracking algorithm are shown in Figs 1 - 4.

As we can see in Fig.1, the dot marks represent different MPCs in different snapshots, and it can be seen that different MPCs are moving. We show the moving paths of MPCs by linking the MPCs in different snapshots. As shown in Fig.1, the algorithm can recognize the moving path correctly when there is only one MPC in each cluster.

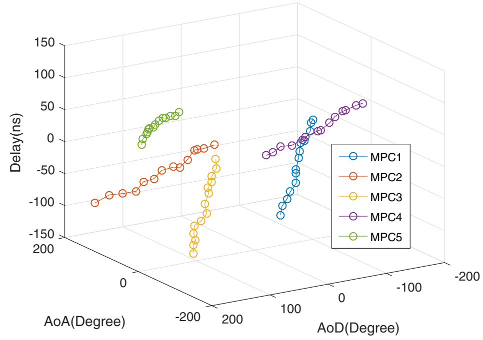

Figure 1. 5 clusters with 1 MPC in each cluster.

Tracking results of 5 clusters with three MPCs in each cluster are shown in the Fig.2. In this scenario, each cluster is consist of three MPCs. Hence, the difficulty of moving path recognition is higher than the first scenario. However, as shown in Fig. 2, the algorithm still works well.

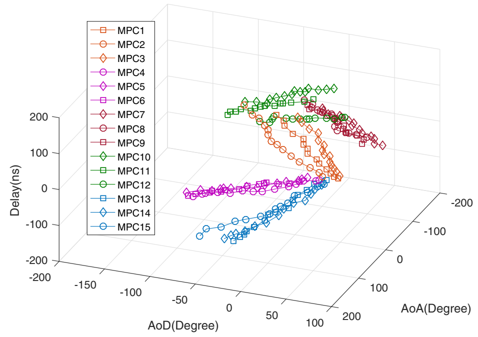

Figure 2. 5 clusters with 3 MPCs in each cluster.

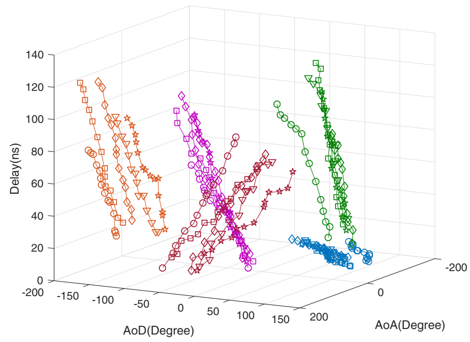

Figure 3. 5 clusters with 5 MPCs in each cluster.

As the number of MPCs in each cluster increases, the difficulty of moving path recognition is higher and the algorithm is more complex because of a larger number of potential paths between different MPCs. Note that the legend is not labeled because there are 25 path in Fig.3. As we can see in the Fig.3, there are some cross moving paths when MPCs are close to each other. However, the tracking algorithm can identify each moving path correctly. In the end, we test a

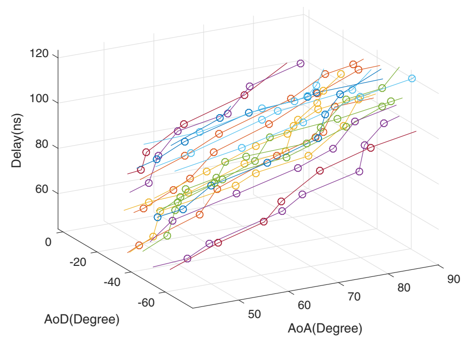

Figure 4. 5 clusters with 20 MPCs in each cluster.

more complicated scenario, where the number of MPCs in each cluster is up to 20. Fig.4 shows the trajectories of one of the five clusters, and to clearly indicate MPCs' trajectories, different trajectories are plotted with different colors. In Fig.4, some MPCs are much closer to each other than its real position in the next snapshot, however, the tracking algorithm can still target the right moving path. This is because different possible paths are weighted by power, and the algorithm pursues the maximum probabilities of the whole paths. However, in this scenario, the running time of algorithm is significantly increased. This is because more MPCs lead to more potential paths. Hence, our future work would be reduceing overhead of the tracking algorithm.

5 Conclusion

A power weighted MPCs tracking algorithm is proposed in this paper. The problem of seeking potential position is solved by using a MAP estimation in a Markov random process. The dynamic trajectories in continuous snapshots are considered, and tracking results show a high recognition accuracy. The tracking algorithm is validated by using simulated dynamic channels. It is found that the tracking algorithm can recognize trajectories correctly even in dense MPC scenarios.

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References

[1] Bello P. Characterization of randomly time-variant linear channels[J]. *IEEE transactions on Communications Systems*, 1963, 11(4): 360-393.

[2] He R, Renaudin O, Kolmonen V M, et al. Characterization of Quasi-Stationarity Regions for Vehicle-to-Vehicle Radio Channels[J]. IEEE Transactions on Antennas and Propagation, 2015, 63(5): 2237-2251.

[3] Yu K, Li Q, Cheung D, et al. On the tap and cluster angular spreads of indoor WLAN channels[C]//Vehicular Technology Conference, 2004. VTC 2004-Spring. 2004 IEEE 59th. IEEE, 2004, 1: 218-222.

[4] Chong C C, Tan C M, Laurenson D I, et al. A new statistical wideband spatio-temporal channel model for 5-GHz band WLAN systems[J]. IEEE Journal on selected areas in Communications, 2003, 21(2): 139-150.

[5] He R, Chen W, Ai B, et al. On the Clustering of Radio Channel Impulse Responses Using Sparsity-Based Methods[J]. IEEE Transactions on Antennas and Propagation, 2016, 64(6): 2465-2474.

[6] Chuang J, Bashir S, Michelson D G. Automated identification of clusters in UWB channel impulse responses[C]//2007 Canadian Conference on Electrical and Computer Engineering. IEEE, 2007: 761-764.

[7] Gentile C. Using the Kurtosis Measure to Identify Clusters in Wireless Channel Impulse Responses[J]. IEEE Transactions on Antennas and Propagation, 2013, 61(6): 3392-3395.

[8] Salo J, Salmi J, Czink N, et al. Automatic clustering of nonstationary MIMO channel parameter estimates[M]. na, 2005.

[9] Czink N, Cera P, Salo J, et al. A framework for automatic clustering of parametric MIMO channel data including path powers[C]//IEEE Vehicular Technology Conference. IEEE, 2006: 1-5.

[10] Zhu F, Wang X, Yu N. Crowd tracking with dynamic evolution of group structures[C]//European Conference on Computer Vision. Springer International Publishing, 2014: 139-154.

[11] Ge W, Collins R T, Ruback R B. Vision-based analysis of small groups in pedestrian crowds[J]. IEEE transactions on pattern analysis and machine intelligence, 2012, 34(5): 1003-1016.

[12] Rubio J C, Serrat J, LĹópez A M, et al. Multiple-target tracking for intelligent headlights control[J]. IEEE Transactions on Intelligent Transportation Systems, 2012, 13(2): 594-605.

[13] He R, Renaudin O, Kolmonen V M, et al. A Dynamic Wideband Directional Channel Model for Vehicle-to-Vehicle Communications[J]. IEEE Transactions on Industrial Electronics, 2015, 62(12): 7870-7882.