A Regional Clustering Method Based on Propagation Similarity for Modeling Cumulative Interference from Large Numbers of Terminals

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Abstract—**To realize Beyond 5G networks, frequency sharing between terrestrial and satellite communication systems is essential. However, in urban environments, it is difficult to evaluate the cumulative interference from a large number of terrestrial wireless terminals to conventional satellite ground stations in real time, due to the massive number and mobility of terminals. This paper proposes an approach to reduce the computational cost of interference estimation by clustering terrestrial terminals. This enables significant reduction in the complexity of interference calculations. Furthermore, we propose a new clustering method based on the similarity of radio propagation characteristics. The method uses standardized RSSI values and terminal positions as features, and applies recursive clustering with dynamic deviation control to minimize propagation variation within clusters. Simulation using real-world terminal distribution data in an urban area demonstrates that the proposed method improves propagation similarity within clusters while maintaining coarser cluster partitioning compared to conventional methods. Validation of interference estimation accuracy using the proposed clustering method will be addressed in future work.**

I. INTRODUCTION

In Beyond 5G (B5G) and 6G systems, the stable and efficient use of radio frequency resources has become a critical challenge. One promising approach to address this issue is spectrum sharing between cellular systems and non-cellular systems [1]. In such inter-system spectrum sharing, the goal is to enable cellular systems to opportunistically access spectrum while ensuring the protection of incumbent systems [2]. In particular, spectrum sharing with satellite and radar systems in high-frequency bands has been actively studied [3], [4].

Accurate modeling of co-channel interference (CCI) is essential to ensure mutual protection between systems sharing the same frequency. Various CCI models have been proposed in previous studies. In the millimeter-wave and sub-terahertz bands, composite interference models from multiple terminals considering antenna directionality have been investigated [5]. Probabilistic models have also been proposed for aggregated interference caused by arbitrary emitters or wireless devices [6]. Interference modeling in device-to-device (D2D) communications, especially under coexistence with primary systems, has been discussed [7]. Interference from 5G TDD systems to radar systems has been modeled in previous studies [8], [9]. In addition, interference from a large number of terrestrial terminals to UAVs in line-of-sight (LoS) environments has also been analyzed [10].

The concept of the Digital Spectrum Twin has been proposed to manage spectrum usage comprehensively in cyberspace and provide appropriate frequency assignments to individual devices [11]. While this concept holds promise for efficient spectrum management, it typically relies on analytical path loss models, which often fail to reflect site-specific propagation conditions, especially in urban environments. In satellite-terrestrial spectrum sharing, some regulatory approaches adopt static spatial protection, such as establishing large-scale quiet zones [12]. Other works estimate mutual interference in Non-Terrestrial Network—Terrestrial Network (NTN—TN) coexistence by geometric distance calculations [13]. New frameworks such as Tool for Enabling Spatial Spectrum Sharing Opportunities (TESSO) have also been proposed for cumulative interference modeling [14].

When considering spectrum sharing between satellite and cellular systems, even weak emissions from cellular terminals may cause significant interference to the highly sensitive satellite receivers. As a result, terminals located far from satellite ground stations can still contribute non-negligible interference, leading to the need to consider a vast number of terminals in interference modeling. While simple path loss models have been used for this purpose [13], they often fail to account for propagation effects caused by buildings and obstructions, resulting in low modeling accuracy. Ray-tracing simulations can provide accurate results by considering site-specific conditions, but the computational cost scales with the number of terminals, making it impractical for large-scale real-time evaluations. Therefore, there is a strong need for interference modeling techniques that are both computationally efficient and accurate.

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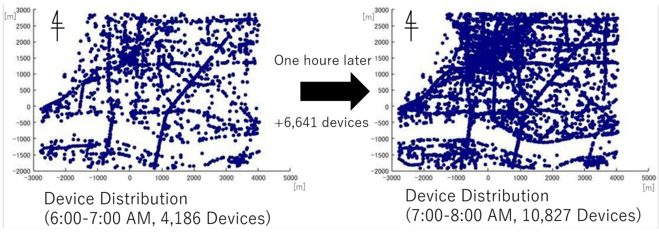

Fig. 1. Device Distribution around Nagano Station on October 1, 2021

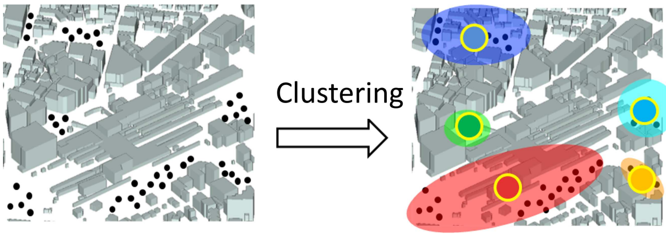

Fig. 2. Illustration of Clustering Concept

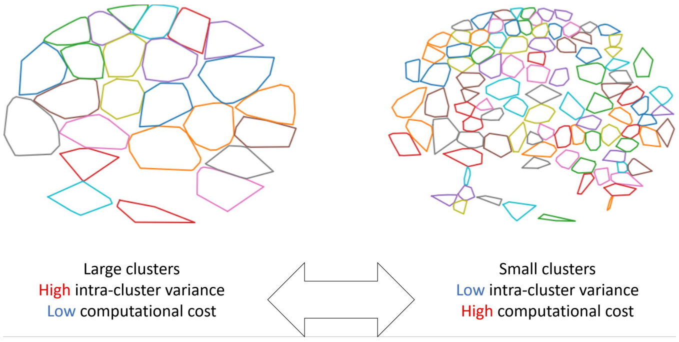

Fig. 3. Effect of Clustering Granularity

To achieve both high accuracy and low computational cost in interference estimation for urban environments, this paper introduces a new framework that approximates propagation effects at the cluster level, rather than evaluating each terminal individually as in conventional methods. By clustering terminals that share similar propagation conditions—such as those influenced by the same building obstructions—and assigning a representative propagation model to each cluster, the proposed approach addresses the trade-off between estimation accuracy and computational efficiency. Furthermore, we propose a novel clustering method that enables dynamic control of cluster size and validate its effectiveness through simulations using real-world terminal distribution data.

II. COMPUTATION-EFFICIENT INTERFERENCE ESTIMATION VIA CLUSTERING-BASED MODELING

This section introduces the core concept of the proposed framework: approximating cumulative interference from a large number of mobile terminals using region-based clustering based on radio propagation characteristics. Instead of evaluating each terminal individually, the proposed approach enables lightweight and scalable estimation through pre-aggregation of terminals.

A large number of terrestrial wireless terminals are deployed in urban environments, and since these devices are often carried by humans, their spatial distribution can vary significantly over time. Fig. 1 shows the distribution of terminals around Nagano Station on the morning of October 1, 2021, based on data provided by AGOOP Corp. Within a single hour, the number of terminals increased by approximately 7,000, resulting in more than a twofold increase in total. This demonstrates the substantial temporal variation in terminal density. Signals emitted from these terminals can serve as sources of interference to satellite ground stations, making it essential to accurately estimate the cumulative interference power for effective frequency sharing between satellite and terrestrial communication systems.

If this estimation were to be performed using conventional radio propagation simulations such as ray-tracing, it would be necessary to simulate all terminals individually and repeat the simulation at regular intervals due to the mobility of the terminals. This would require a large amount of computational resources and time.

As a lightweight alternative, an approach as illustrated in Fig. 2 can be considered, in which terrestrial terminals are clustered, and a representative propagation model is assigned to each cluster. This enables the influence of terminals to be efficiently estimated at the cluster level during interference calculation, significantly reducing the computational burden per estimation.

III. PROPOSED CLUSTERING METHOD

For the framework introduced in the previous section to function effectively, the terminals within each cluster must be well approximated by the assigned representative propagation model. If a cluster contains a large number of terminals with differing obstruction environments, the deviation from the representative model may become significant, potentially leading to a substantial degradation in the accuracy of interference estimation. Therefore, it is desirable to divide terminals into clusters such that each cluster contains terminals that are not only geographically close but also share similar propagation characteristics.

The granularity of clustering also significantly affects the effectiveness of this approach. As illustrated in Fig. 3, if the clustering is too coarse in an attempt to reduce computational cost, the estimation accuracy may deteriorate due to the inclusion of terminals with dissimilar propagation characteristics in the same cluster. On the other hand, if the clustering is too fine in order to increase propagation similarity within clusters, the cost of constructing propagation models and performing interference estimation for each cluster becomes substantial. Therefore, a clustering method that balances intra-cluster propagation similarity with clustering granularity is required.

Therefore, we propose a clustering method called Dynamic Deviation-Based Clustering. The flow of the algorithm is

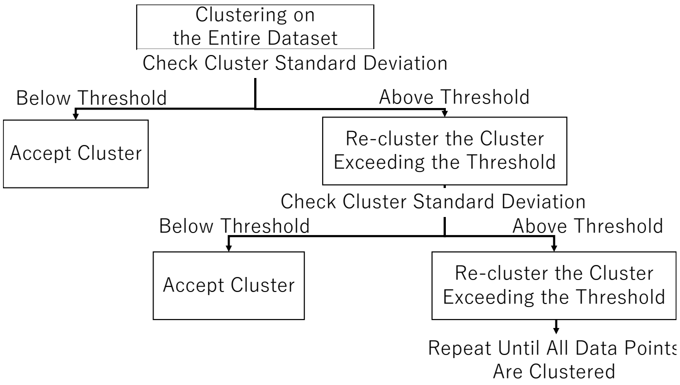

Fig. 4. Dynamic Deviation-Based Clustering Flow

shown in Fig. 4. This algorithm uses standardized features: the x-coordinate [m], y-coordinate [m], and RSSI [dBm]. The RSSI values represent the received power at the interference source when a signal is transmitted from the terminal, and are obtained through site-specific ray-tracing simulations.

Although the ultimate goal is to evaluate the interference power received at a satellite ground station from terrestrial terminals, in this study we simulate signal reception at the terminals in order to obtain the RSSI values used for clustering. This is justified by the reciprocal nature of radio propagation: since the propagation path remains unchanged when the transmitter and receiver are swapped, the overall path loss also remains the same. As a result, the RSSI used as a feature reflects the propagation loss—including distance attenuation and obstruction effects—from the interference target to each terminal, making it suitable for clustering based on propagation similarity.

If clustering were performed using only propagation characteristics, such as RSSI, terminals would be grouped solely based on their received signal levels. However, in that case, geographically distant terminals could be classified into the same cluster. As mentioned earlier, since terminals are typically carried by people, their distribution changes over time. If terminals that are geographically unrelated are clustered together, such temporal changes in distribution may lead to imbalances within clusters.

On the other hand, by incorporating geographic information —specifically the x- and y-coordinates—along with RSSI as clustering features, terminals that are geographically close are more likely to be grouped into the same cluster. This approach makes the clustering more robust to changes in terminal distribution over time, allowing such changes to be interpreted more naturally as variations in the number of terminals per cluster.

The pseudocode for the proposed algorithm is shown in Algorithm 1. The process begins by performing clustering on the entire dataset. A threshold is set on the standard deviation of RSSI within each cluster, and the generated clusters are evaluated against this criterion. Clusters that satisfy the threshold condition are accepted as they are. For clusters that do not meet the condition, their data are re-clustered recursively until the standard deviation falls below the threshold.

Algorithm 1 Dynamic Deviation-Based Clustering

Require: Clustering function `ClusteringFunc`, Device $D = \{(x_i, y_i, \mathrm{RSSI}_i)\}$, threshold T, initial cluster count K_0

Ensure: Set of clusters C satisfying intra-cluster deviation $\leq T$

```
Initialize empty cluster set $C \leftarrow \emptyset$
Initialize data $d \leftarrow D$
while $d$ is not empty do
    $is_success \leftarrow$ false
    $K \leftarrow K_0$
    while $is\_success$ is false do
        $Clusters \leftarrow$ ClusteringFunc$(d, K)$
        for all $c \in Clusters$ do
            if $\mathrm{StdDev}(c.\mathrm{RSSI}) \leq T$ then
                Add $c$ to $C$
                Remove $c$ from $d$
                $is\_success \leftarrow$ true
            end if
        end for
        $K \leftarrow K + 1$
    end while
end while
return $C$
```

Data belonging to clusters that do not satisfy the threshold condition are further subdivided. In the extreme case where a cluster consists of only a single terminal, the standard deviation becomes zero, guaranteeing that the condition is satisfied. Thus, the algorithm is guaranteed to terminate.

Since the RSSI standard deviation within each resulting cluster is constrained to be below the predefined threshold, similarity in propagation characteristics among terminals within each cluster is ensured. Furthermore, clusters that satisfy the condition in the early stages of the algorithm tend to contain a larger number of terminals. As a result, the proposed method is expected to achieve high clustering precision while keeping the overall clustering granularity low.

IV. SIMULATION SETTINGS AND EVALUATION PROCEDURE

We conducted simulations to verify the effectiveness of the proposed Dynamic Deviation-Based Clustering method. The simulation parameters are summarized in Table I. Wireless InSite was used to perform a ray-tracing simulation, in which a transmitter was placed 30 meters above ground level at the Faculty of Engineering, Shinshu University, and terminals located within a 1.5 km radius received the signals. The terminal distribution data used in this study were provided by AGOOP Corp. and correspond to the period from 7:00 AM to 10:00 AM on October 1, 2021. A total of 10,107 terminals with received signal data were included in the simulation.

In this study, we evaluate three different clustering methods:

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Number of terminals	10,107
Antenna type	Omnidirectional
Frequency band	27 GHz
Transmission power	20 dBm
Initial number of clusters	6

TABLE II
THRESHOLD VS. NUMBER OF CLUSTERS

Threshold [dB]	Number of clusters
6	49
7	35
8	27

1) Dynamic Deviation-Based Clustering (Proposed Method)
2) K-means++ using RSSI and coordinates as features (Baseline 1)
3) K-means++ using only coordinates as features (Baseline 2)

Baseline 2 performs clustering using only the x- and y-coordinates as features with the K-means++ algorithm. This method groups geographically close terminals and is considered one of the most common conventional approaches for spatial partitioning.

Baseline 1 extends Baseline 2 by incorporating RSSI as an additional feature, along with the x- and y-coordinates, in the K-means++ algorithm. By including the received signal strength, this method aims to improve the similarity of propagation characteristics within each cluster.

In the simulation, the proposed method internally uses the K-means++ algorithm as the clustering technique.

The Proposed Method is evaluated by varying the threshold value and analyzing the resulting cluster characteristics. The number of clusters used in Baseline 1 and Baseline 2 is set to match the number of clusters generated by the Proposed Method for each threshold. The correspondence between the threshold values and the number of clusters is shown in Table II. This normalization is applied because a larger number of clusters, i.e., finer clustering, generally leads to higher similarity in propagation characteristics within each cluster. The number of clusters remains below 50, meaning that the original 10,107 terminals are compressed to less than one two-hundredth. This compression is expected to significantly reduce the computational burden of interference estimation.

V. SIMULATION RESULTS

Figs. 5 to 7 show the clustering results with a threshold of 6 dB. These figures present a cropped view around Nagano Station, where each point represents a terminal, and terminals in the same cluster are indicated by a common color. Fig. 7, corresponding to Baseline 2, uses only the x- and y-coordinates as features. As a result, the clusters are neatly partitioned geographically, but propagation characteristics are not considered.

Comparing Fig. 5 (Proposed Method) with Fig. 6 (Baseline 1), we observe that a region on the left side is grouped into two clusters (red and reddish-purple) in the Proposed Method, while the same region is divided into four to five smaller clusters in the baseline method. This demonstrates that the Proposed Method contributes to coarser clustering while preserving similarity in propagation characteristics.

Fig. 5. Clustering Map (Proposed Method)

Figs. 8 to 10 show the cumulative distribution functions (CDFs) of the RSSI standard deviation for each cluster, categorized by clustering method. In the Proposed Method, all clusters satisfy the threshold for every threshold setting. In Baseline 1, approximately 80% of clusters fall within the threshold, but some clusters still exhibit large standard deviations. In Baseline 2, approximately 90% of clusters exceed the threshold by around 5 dB.

Furthermore, at the 100% point of the CDF, the Proposed Method outperforms Baseline 1 by up to approximately 6 dB at a threshold of 8 dB, and outperforms Baseline 2 by up to approximately 15 dB at a threshold of 6 dB.

Fig. 11 illustrates the relationship between the RSSI standard deviation and the number of terminals per cluster when the threshold is set to 6 dB. Clusters located in the upper-left region of the plot—those with low RSSI standard deviation and a large number of terminals—are considered preferable, as they indicate high similarity in propagation characteristics while maintaining cluster size.

In the Proposed Method, such favorable clusters exist: they meet the threshold condition and include a large number of terminals. In contrast, Baseline 1 and Baseline 2 tend to produce more clusters with higher RSSI standard deviation and fewer terminals. These results indicate that the Proposed Method is capable of forming larger clusters while suppressing variations in propagation characteristics.

VI. CONCLUSION

In this study, we proposed a new framework for estimating interference from a large number of terrestrial terminals in urban environments with practical computational cost by introducing region-based clustering based on propagation similarity.

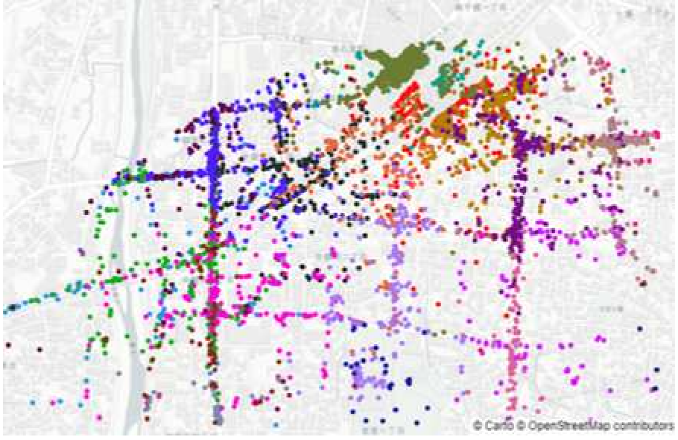

Fig. 6. Clustering Map (Baseline 1: RSSI + Position)

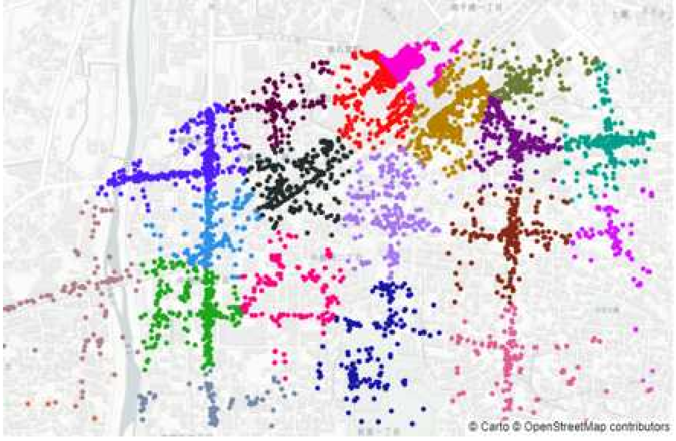

Fig. 7. Clustering Map (Baseline 2: Position Only)

The most significant contribution of this work is that it presents a pathway for evaluating interference at the cluster level using representative models, instead of assessing propagation individually for each terminal.

Furthermore, we designed a new clustering method that simultaneously achieves coarse spatial partitioning while suppressing variation in propagation characteristics within each cluster. Through simulations using real-world terminal distribution data, we demonstrated its effectiveness compared to conventional methods.

This study focused on the evaluation of clustering accuracy. Evaluation of interference estimation accuracy using the resulting clusters remains as future work. In future research, we plan to investigate the effectiveness of the proposed method for interference estimation and explore its application to real-time interference assessment.

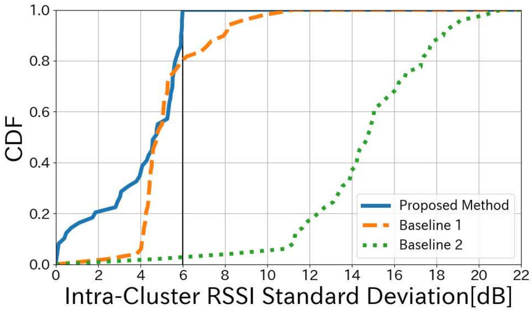

Fig. 8. CDF of RSSI Standard Deviation for Each Clustering Method (6 dB Threshold)

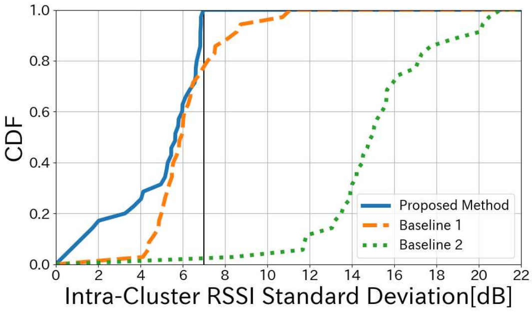

Fig. 9. CDF of RSSI Standard Deviation for Each Clustering Method (7 dB Threshold)

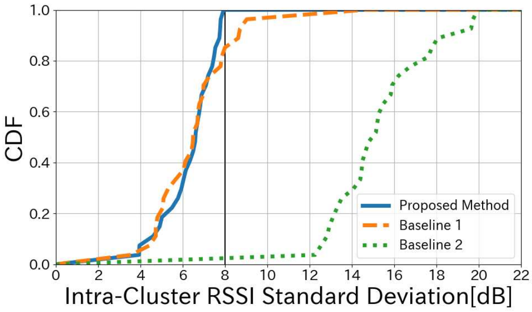

Fig. 10. CDF of RSSI Standard Deviation for Each Clustering Method (8 dB Threshold)

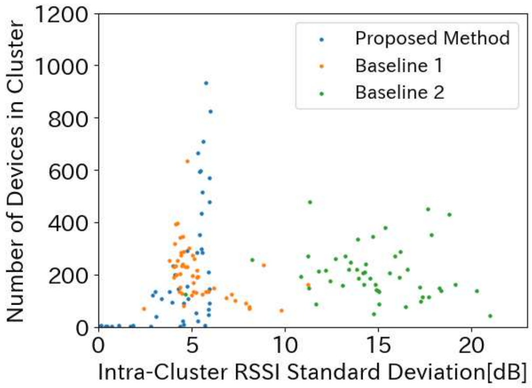

Fig. 11. RSSI Standard Deviation vs. Number of Terminals (6 dB Threshold)

ACKNOWLEDGMENT

This work was supported by JSPS KAKENHI Grant Number JP24K00881. The authors would also like to thank Mr. Akihisa Yoshiba for his valuable advice.

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