Shared Decision Making Using Distribution Estimation of Same Frequency Interference in 5G*.

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***Abstract*—In this study, the cumulative probability distribution (CDF) of PUSCH (Physical Uplink Shared Channel) Throughput, which is the throughput of the lower layer in local 5G, is estimated by Gaussian kernel density estimation in an environment where frequency sharing is assumed between different systems. The CDF was estimated by the Gaussian kernel density estimation method and established as an acceptable criterion for frequency sharing. Experimental results show that the proposed method is more accurate than the conventional method.**

***Index Terms*—Frequency Sharing, Same Frequency, Distribution Estimation, Kernel Estimation Method**

I. Introduction.

The explosive growth of radio frequency traffic for next-generation mobile communications has made it an important issue to cope with the tightness of frequency resources [7]. Frequency sharing, in which multiple systems share the same frequency resources to increase the efficiency of spatial and temporal utilization, is attracting attention as an effective solution to this problem [8]. In order to share frequencies among multiple systems, interference from one system to the other must be properly controlled so that both systems can establish communications with the required communication quality. There are two ways to control interference: one is to ensure spatial separation between the systems to sufficiently suppress interference [9], and the other is to control interference over time by using the frequency resources available when the other system is not in use [10]. In interference control that ensures spatial separation, the propagation distance of the interfering wave is estimated using a radio propagation model equation, and the radio transmission power and antenna directivity are controlled so that the interference from other systems is kept below a specified value. Ordinary radio propagation models are generalized and do not take into account the presence of shields that exist in the actual propagation environment, such as buildings that have a shielding effect on radio waves. As a result, there is a difference between the estimated interference and the actual interference. Such a difference in the given interference causes serious degradation of communication quality for other systems. To avoid this, the interference power is set higher than expected, and a margin is provided. As a result, even in the case of a difference between estimated and actual given interference, the generation of interference exceeding the assumption can be suppressed and degradation of communication quality can be avoided. The margin setting is decided upon consultation between systems sharing frequencies, but conservative sharing guidelines result in excessively large margins. As a result, the spatial separation distance required for sharing becomes large and the time available to use frequency resources is limited, and improvement in frequency utilization efficiency cannot be realized. Therefore, a possible way to avoid interference is to provide a mechanism that monitors the communication quality of the system sharing the frequency while it is actually communicating, and if the quality deteriorates beyond a certain level, it notifies the user that serious interference has occurred. Such a mechanism for protection against interference can suppress the margin required to a small extent, and safe frequency sharing can be achieved through interference protection by means of notification of the occurrence of interference.

In this study, the estimation is performed with the user experience of frequency sharing in mind. Therefore, we estimate the distribution using PUSCH Throughput as an identifier as the QoS of the user experience. Specifically, the proposed method focuses on estimating the worst Throughput value. In real environments, fluctuations in interference power occur due to fading and other factors. For the user, a drop in the Throughput worst-case value has a stronger impact on the user experience than fluctuations in the Throughput average value. The proposed method in this study first defines ”Normal” and ”Anomaly” data based on a comparison of tolerance limits (acceptable values) and Throughput worst-case values. Next, the data are divided and the statistical distribution is estimated using Gaussian kernel density estimation. Finally, the estimated values are compared to the allowed values and classified as ”Normal” or ”Anomaly. The proposed method was confirmed to show a significant improvement in accuracy compared to the conventional method. This study uses measurement data from actual equipment experiments, and the details of the experiments are described in the literature [6].

Section 2 describes the proposed method, Section 3 compares the estimation results of the proposed method with those of the conventional method, and Section 4 summarizes this study and discusses future prospects.

II. Proposed Method

A. Throughput Worst Value

Figure1 shows a flowchart of the proposed method in this study. In this study, we consider the frequency sharing judgment in the user experience to be important, and estimate the drop in the worst-throughput value. First, the definition of the worst-throughput value is presented. The CDF graph of PUSCH Throughput at each interference power obtained in this experiment is shown in the figure2. The Throughput at CDF 0.1 in the figure2 is calculated for each interference power. In this study, the calculated value of Throughput is called the worst Throughput value.

B. Definition of tolerances and data

Next, we define a 15% drop from the normal state Throughput in CDF0.1 as the tolerance limit, which we call the tolerance value. In addition, we define the data obtained in the experiment as ”Normal” data and ”Anomaly” data by comparing this tolerance value with the worst Throughput value described above. Specifically, when the allowable value is 85.877487 [Mbps] and the output power from the signal generator is -40 [dBm], the worst throughput value is 98.396999 [Mbps], which is defined as ”Normal” data. On the other hand, when the output power from the signal generator is -5[dBm], the worst Throughput value is 45.83277750[Mbps], which is defined as ”Anomaly” data. In this way, ”Normal” or ”Anomaly” is defined for each interference power.

C. Data Division

In this study, with the aim of speeding up frequency sharing decisions, the observed data are divided and the statistical distribution is estimated by Gaussian kernel density estimation. The figure3 below shows an illustration of data partitioning. For example, when the number of data partitions is 10, the first 1 to 10 samples are used for estimation as shown in the figure3. Next, estimation is performed using samples 11 to 20. This process is repeated to check the correctness rate between the actual measured values in CDF0.1 and the estimated values in CDF0.1. The actual data obtained is divided into 10, 20, ..., and 100 segments, using 16,400 samples in total.

D. Gaussian kernel density estimation

In this study, we assumed that the trend of throughput is Gaussian, and used Gaussian kernel density estimation, which returns a probability density value, to perform the estimation. Specifically, we used the module ”gaussiankde” in the python scipy.stats library to perform the estimation.

A CDF graph was created from the probability density values obtained using Gaussian kernel density estimation, and the worst throughput value in CDF0.1 was output as an estimated value. The obtained estimates are compared with the allowed values. Specifically, if the estimated value is 91.5 [Mbps] as a result of estimation using a portion of the data defined as ”Normal,” the estimated value is judged to be ”Normal” because the Throughput is greater than the allowable value. This means that the data defined as ”Normal” was estimated as ”Normal”. On the other hand, when the estimated value is 74.7 [Mbps], the throughput is smaller than the allowable value, and therefore, it is judged to be estimated as ”Anomaly”. This is an error because the data defined as ”Normal” was estimated as ”Anomaly”.

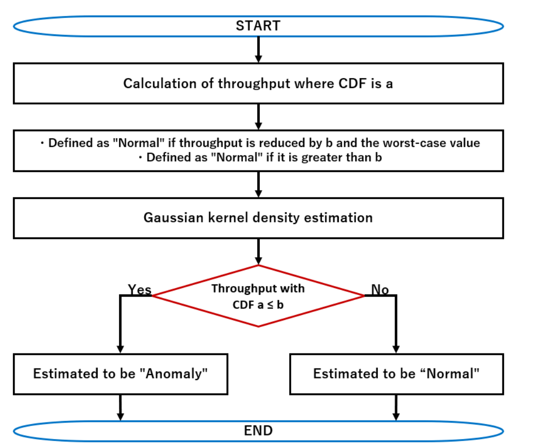

Fig. 1. Flow Chart

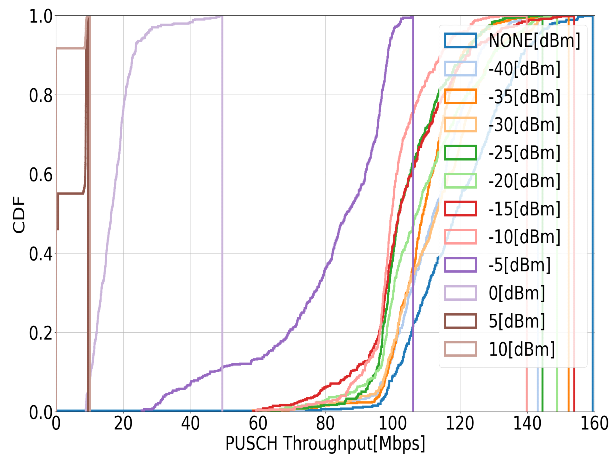

Fig. 2. CDF Graph in PUSCH Throughput

E. Comparison with conventional methods

In this study, we compared the conventional method with the proposed method. In the conventional method, the detection of an event that occurs 1 out of 10 times is considered when making an evaluation in CDF0.1. In other words, if an event is incorrectly estimated 2 out of 10 times in the estimation results, it is all incorrectly estimated. Specifically, when the number of divisions is 10, all 10 judgment results are considered erroneous when two or more erroneous estimates exist among the 10 judgment results.

This study shows the difference in estimation results between the conventional method and the proposed method using Gaussian kernel density estimation, and clarifies the improvement in estimation accuracy using the proposed method.

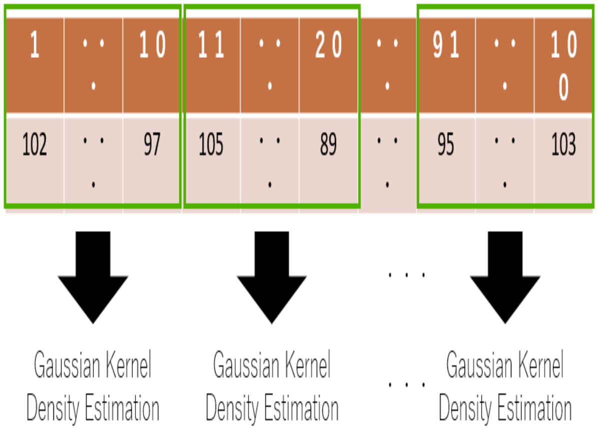

Fig. 3. Imaged figure of data division

III. Estimated Results

The tableI shows the results of the estimation in terms of a mixture matrix. From such a mixture matrix, we used Accuracy and Recall as two evaluation indices. The formulas for the two indices are shown below. In this study, Recall is defined as ”Anomaly” while the estimated value is also defined as ”Anomaly” in the case where Recall was actually ”Anomaly”.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

$$Recall = \frac{TN}{FP + TN} \tag{2}$$

The results for each indicator for the number of divisions from 10 to 100 are plotted in the figure4. The horizontal axis indicates the number of divisions; the larger the value, the fewer samples were used in the estimation. The vertical axis shows the value of each score. The figure4 shows that the proposed method is superior in both evaluation indices. In addition, it is confirmed that the Recall score tends to decrease as the number of divisions increases. In addition, the proposed Gaussian kernel density estimation method has a high accuracy of over 88% in terms of accuracy.

In addition, the accuracy of the model itself was evaluated using KL divergence. The horizontal axis shows the data labels of the acquired data, corresponding to the output power from the signal generator. The vertical axis shows the value of KL divergence. in the figure5. The figure5 shows that there is no significant difference between the distribution based on Gaussian kernel density estimation and that of the measured data. Although the KL divergence of the data defined as ”Analytical” is relatively large, it is less than 1.5 for all data labels, confirming the high estimation accuracy of the Gaussian kernel density estimation model in estimating the throughput distribution.

TABLE I

MIXTURE MATRIX

		Real	
		Normal	Anomaly
Predict	Normal	TP	FP
	Anomaly	FN	TN

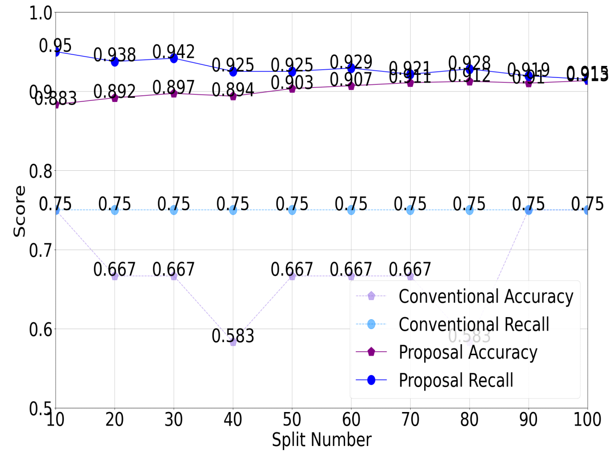

Fig. 4. Estimated Results

IV. Summary and Future Prospects

In this study, the value at the bottom 10% point in the CDF graph of PUSCH Throughput was defined as the worst Throughput value, and the value at which Throughput decreased by 15% from the normal state was used as the acceptable limit value, which was estimated using Gaussian kernel density estimation. In order to speed up the frequency sharing decision, estimation was performed using only a portion of the obtained data, and as a result, a high accuracy of more than 88% Accuracy was confirmed.

As a future perspective, the reason for a certain degradation in accuracy was assumed to be that the trend of the throughput was Gaussian, but there may be a discrepancy with the actual distribution. Therefore, modeling the exact probability distribution of the Throughput distribution is an important issue to be considered.

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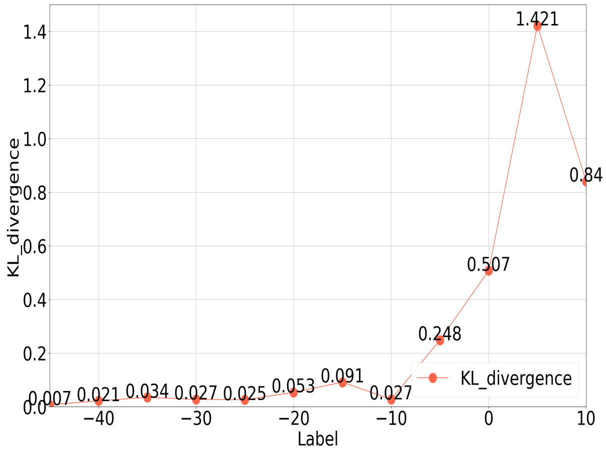

Fig. 5. KL divergence

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