Characterization of Discrimination of Number of Signal Collision Sensors Using Spectral Fluctuation Caused by Frequency Offset in Physical Wireless Parameter Conversion Sensor Networks

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***Abstract*—Physical Wireless Parameter Conversion Sensor Networks (PhyC-SN) is converts sensor information into a carrier wave and transmits it to aggregate information from many sensors at a high speed. The authors established a method to detect multiple sensors accessing within a specific frequency by utilizing frequency offsets to check whether the signals of multiple sensors collide within the frequency. However, it is difficult to identify the number of sensors accessing at the same time. In this study, we established a method to use fluctuations in the received energy spectrum due to sensor-specific frequency offsets as a feature to identify the number of sensors and clarified the identification accuracy for up to four transmitting sensors.**

***Index Terms*—PhyC-SN, frequency offset, window function, Random Forest, collision detection**

I. Introduction.

In recent years, the development of wireless communication technology has accelerated the spread of IoT [1]. The IoT has led to active research on accurate and high-speed communication technologies to realize environmental monitoring [2]. As a high-speed communication method, simultaneous multiple connections, which is a technology to communicate from many sensors at the same time, has attracted attention. In the conventional packet communication method, in order to recover individual sensor information accurately and with high dimensionality, IDs for each sensor are assigned to packets and collision avoidance is performed for each sensor [3]. Therefore, as the number of sensors increases, the communication time and cost increase. In this paper, we focus on a Physical Wireless Parameter Conversion Sensor Networks (PhyC-SN) that can aggregate information from a large number of sensors [4]. This eliminates the ID information that indicates the source of each transmission and reduces the communication overhead. Therefore, PhyC-SN is a communication method that improves communication speed and reduces communication volume, although the source of the aggregated information cannot be identified because the sensor ID cannot be obtained. As an example of the use of PhyC-SN, a new communication method, a method of positioning the source of radio emission has been proposed based on the distribution of sensor information, which is the relative relationship between simultaneously notified sensor information [5].

When multiple sensors acquire the same sensor information in PhyC-SN, each sensor transmits on the same channel. A channel here is a frequency band that separates the available frequency bands, and one channel corresponds to one sensing data. In receiver processing, the number of sensors that have transmitted is identified by using the feature that the amount of energy in the received signal for each channel increases with the number of sensors that have transmitted [6]. In this case, there is a method to identify the number of sensors by evaluating the amount of energy at each frequency and setting a threshold value according to the number of sensors. However, if fluctuations in power occur due to multipath fading or out-of-phase synthesis of signals from multiple sensors, the identification accuracy is greatly degraded. On the other hand, by using not only the power characteristics but also the variance value of the phase transition of the signal for identification, high identification accuracy can be achieved when the number of transmitting sensors is two or less [7]. However, with this method, the identification accuracy remains degraded when the number of transmitting sensors is three or more, and the accuracy of the distribution of sensor information when the number of aggregate sensors increases is not high. Therefore, a method with high identification accuracy is required even when the number of sensors increases.

In this study, we evaluated the discrimination accuracy of PhyC-SN with the addition of new features when the number of collision sensors was increased to four. Long interval FFT

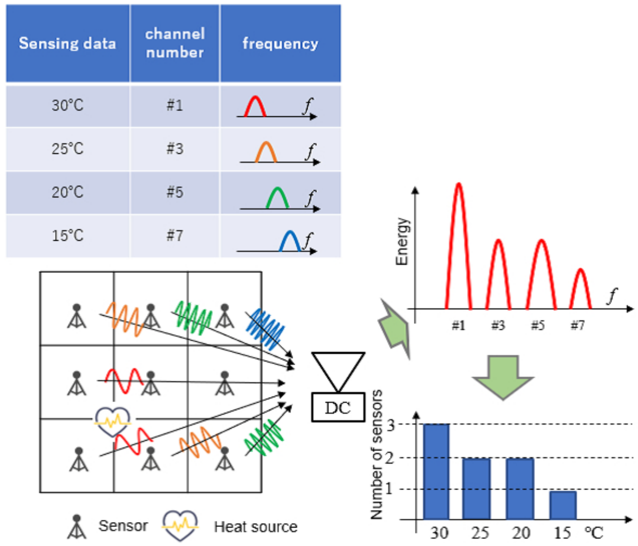

Fig. 1. Schematic diagram of PhyC-SN

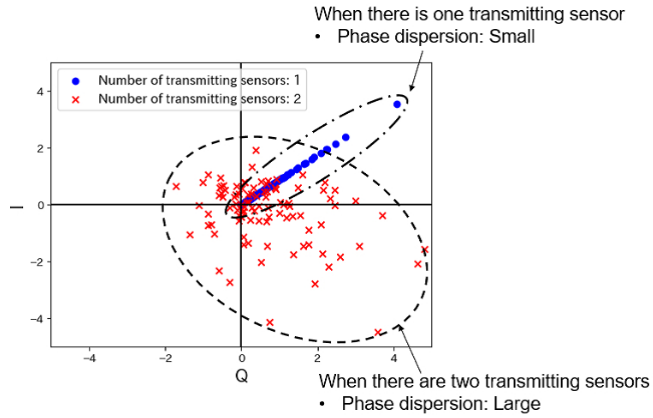

Fig. 2. Arrangement of signal points per number of sensors

was performed, and the frequencies that could be visualized were subdivided as the frequency resolution of each channel was improved [8]. From these frequencies, four new features, kurtosis, skewness, number of peak points, and energy value of each frequency component, were added to improve the discrimination accuracy.

II. Sensor number identification by PhyC-SN

A. PhyC-SN

An overview of PhyC-SN is shown in Figure 1. The first is to create a correspondence table linking sensing data and transmission channels. In Figure 1, the sensing data is assigned to each channel as temperature information. Second, sensors in the observation area send sine waves of the frequency of the channel corresponding to the sensing data to the aggregation station, and the aggregation station processes the signals from the third and subsequent steps. The fourth process reconstructs the sensing data and the number of sensors based on the correspondence table created in the first process, and obtains statistical data.

B. Collision Detection

In PhyC-SN, power was used to identify the number of sensors. However, various factors in wireless propagation, such as multipath fading and out-of-phase composition of transmitted signals from multiple sensors, cause the power to fluctuate, degrading the identification accuracy. Therefore, the authors proposed a collision detection method that adds phase variance as a new feature to identify up to two sensors [7]. The first method utilizes the frequency offset that occurs spontaneously for each sensor. Figure 2 plots the delayed detection signal points on the IQ plane according to the number of sensors. In the case of one sensor, the signal points show the same amount of phase transition due to a single frequency offset. In the case of two sensors, two frequency offsets are included, so that the signal points show variations due to the power difference between the signals of each sensor. These are used as the variance values to create features that are superior for discrimination. Second, by making the signal points for which the variance values are calculated selective [9], we created a feature that is more dominant for discrimination. The third is the suppression of intercarrier interference by using a long interval FFT with a Blackman-Harris window. Intercarrier interference must be suppressed because of the natural frequency offset. Therefore, we use a long-interval FFT and a Blackman-Harris window [8].

C. Identification of the number of collision sensors

The authors had discriminated up to two sensors, but the accuracy of discrimination for three or more sensors was not high. In this study, we improved the identification accuracy by adding new features. The figure 3 shows the energy value of each frequency in one channel when the long-interval FFT is performed. The long interval FFT improves the frequency resolution and allows visualization of multiple frequencies within a single channel. In Figure 3, 99 frequencies are subdivided within a single channel, and this is the case for three transmitting sensors. Each transmitting sensor has a large peak, which can be seen as a separate peak due to the frequency offset of each sensor. The energy per frequency subdivided in the channel by the long interval FFT is collectively defined as the energy spread. This energy spread was converted into three indices and utilized as features. The first is kurtosis. The kurtosis is a statistic that measures the sharpness of the spectrum within a channel. When the number of transmitting sensors is large, the kurtosis tends to be low because of the spread of the spectrum in the channel. The second is skewness. Skewness is another statistic that measures the bias in the channel. When the number of transmitting sensors is small, the probability that the spectrum in the channel is biased to the left or right is high, and the value tends to be low. The third is the number of peak points in the spectrum, which depends on

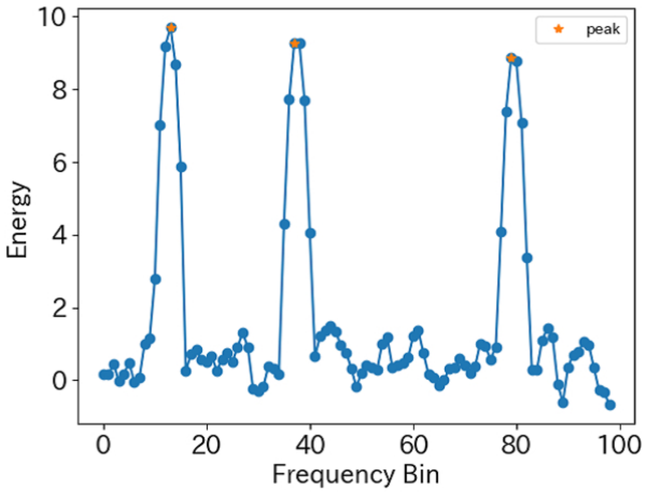

Fig. 3. Energy value per frequency BIN within one channel

the number of sensors, since each sensor has a higher power. The ”peak” in the figure 3 indicates the peak point, and since there are three transmitting sensors, the number of peak points is also three. The three features, kurtosis, skewness, and peak point number are added as features to discriminate the number of sensors, since they tend to be different depending on the number of sensors.

III. Simulation Evaluation

A. simulation parameters

The simulation environment was created using Matlab provided by MathWorks. The simulation parameters are shown in Table I. The radio environment is assumed to be a Rayleigh fading environment with four receiver antennas in the aggregate. The frequency offset is generated by a uniform random number. The number of transmitted symbols is 100, and the FFT interval is the number of transmitted symbols minus 1, so the long-interval FFT interval is 99 symbols. The window function is a Blackman-Harris window. The number of transmitting sensors is limited from 0 to 4. In this case, only one transmission channel is used, and inter-carrier interference is assumed to have no effect. Six features are used for identification: energy value, phase variance, energy spread, kurtosis, skewness, and peak point number. Random Forest is used as the classifier.

Power detection and collision detection are used as conventional identification methods. We compared the discrimination accuracy by increasing the number of features between the conventional method and the proposed method.

B. Feature Analysis

Here, we show the trend of the features when the number of transmitted symbols is 100 and the SNR is 20 dB. In Figure 4, the distributions of kurtosis and skewness are shown by box-and-whisker plots according to the number of sensors. Both of

TABLE I
SIMULATION PARAMETERS

Data type	Data
Number of receiving antennas	4 antennas
Fading environment	Rayleigh fading
Frequency offset	[-0.4 0.4] uniform random number per sensor
Number of transmitted symbols	100 symbols
Window function	Blackman-Harris window
Number of transmitting sensors	0 - 4

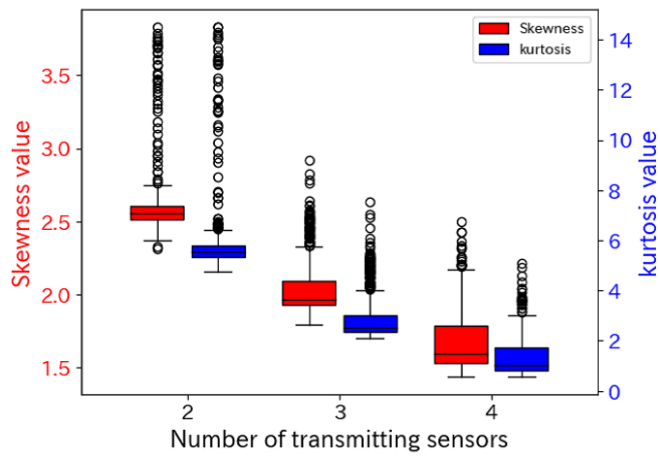

Fig. 4. Box-and-whisker diagram of kurtosis and skewness for each sensor

the features tend to become smaller as the number of sensors increases. Figure 5 shows the number of peak points detected for each number of sensors. The number of sensors and the number of peak points roughly coincide, but there are cases where the number of peak points is smaller than the number of sensors. This may be due to the fact that the difference in frequency offsets between sensors is so small that two spectral peaks overlap and appear as a single peak. Figure 6 shows the difference in the importance of the features used to identify the transmitting sensors. The order of the features used for identification is from the top to the bottom. The size of each color indicates the importance of the feature for each number of transmitting sensors. In this case, the importance of the sharpness is the highest, indicating a high importance when there is a transmitting sensor. However, when there is no green transmitting sensor, the importance of the kurtosis is not so high. When there is no transmitting sensor, the importance of the energy value is the highest. The feature of phase dispersion is also important for the identification of a single transmitting sensor. The kurtosis, skewness, and the number of peak points, which are newly added as features in this study, are highly important and necessary for identification.

IV. Simulation Results

The simulation results are shown in Fig. 7.”Conventional method 1” is power detection, ”Conventional method 2” is

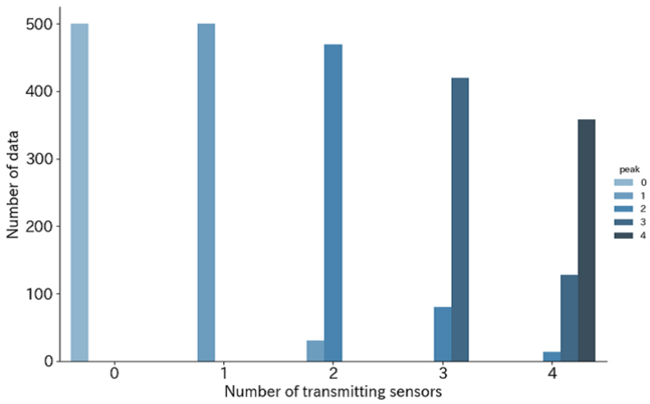

Fig. 5. Number of peak points per sensor

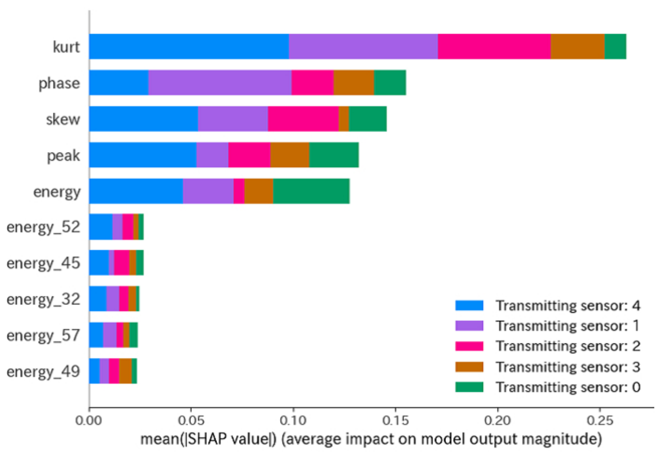

Fig. 6. feature importance

collision detection, and "Proposal method" is the proposed method with the addition of four features from collision detection: energy spread, kurtosis, skewness, and peak point count.

The following is a plot of the relationship between SNR and discrimination accuracy from the three methods. The proposed method showed higher discrimination accuracy than the two conventional methods .In addition, the identification accuracy of the proposed method exceeds 90% when the SNR is more than 8, while the identification accuracy of the conventional method cannot exceed 80%.

V. Summary

Identification of the number of collision sensors in PhyC-SN was possible only up to two sensors. In this study, by adding four new features, we were able to achieve more than 90% identification accuracy up to four sensors. The discrimination accuracy is not perfect, but it is still high. Future tasks are to further improve the discrimination accuracy and to increase the number of sensors that can be discriminated.

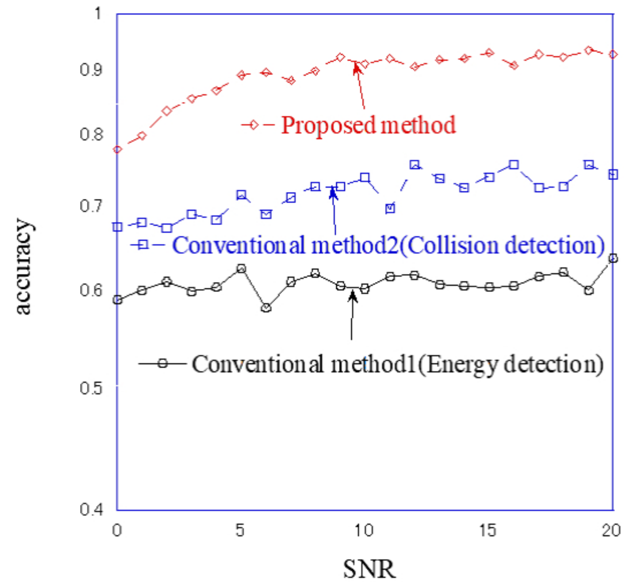

Fig. 7. Identifying success rates

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