Data Separation Technique using Spatial Correlation of Sensing Results for Physical Wireless Parameter Conversion Sensor Networks

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***Abstract*—Wireless sensor networks (WSN) are attracting much attention for using various applications. As a result, the requirements of WSN are widely spread, such as low latency, affordability of a lot of sensors, and super long life. A physical wireless parameter conversion sensor networks (PhyC-SN) has ability for real time data collection and accepting the simultaneous access from a lot sensors. Since each sensor does not send any ID information to fusion center (FC), FC cannot specify the information source of each sensing result. The data separation technique based on data tracking is useful for separating data group from the common information source but it fails to track the data, where the failure of data separation is error tracking. This paper proposes the novel detection technique based on the special correlation among sensing results for detecting error tracking. We confirm the accuracy of the proposed detection technique by computer simulation and experimental evaluation.**

I. INTRODUCTION

Owing to an extension of wireless communication technology, wireless sensor networks (WSN) for collecting sensing results are also significantly extending [1]. The applications of WSN are widely spread, such as agriculture, factory industry, smart grid, robotics and automatic vehicles. As a result, the requirements for WSN are also widely spread. For example, long life time, highly low complexity, real time, and affordability of a lot of sensors ' accesses are given. Although the packet access scheme is usually used for WSN, it may not satisfy these requirements. In the packet access scheme, the carrier sense multiple access (CSMA) and ALOHA are available for wireless access [2]. However, these cause delay due to the function of avoiding packet collision and thus these are lack of real time. When a lot of sensors access to the fusion center, the packet collision is so serious that the throughput performance are degraded. Therefore, the packet access scheme could not afford a lot sensors.

Recently, a physical wireless parameter conversion sensor network (PhyC-SN) is a novel wireless access scheme for WSN [3]. In the PhyC-SN, the frequency modulation scheme is used for informing a sensing result and a fusion center (FC) can recognize all the sensing results by spectrum detection in accordance with the relationship between the value of sensing result and the frequency number of spectrum. As a result, the Phy-C SN is suitable for real time communication and it has affordability for a lot of sensors. It cannot specify the information source of each sensor because each sensor does not send any ID information to FC. We have ever proposed the separation technique of sensing results whose information source is common [4]. The proposed scheme pays attention to the continuity of sensing result and thus the data tracking technique, such as Kalman filter, is useful for separating the sensing results with common information source [4]. Therefore, when the ID of information source is sent to the FC in advance, the information source of all the data can be specified from the separated sensing result. However, if some sensing results are near together, the FC can recognize the sensing result as the different group, where it is referred to as error tracking. Once error tracking occurs, a lot of sensing results are recognized as the wrong information source. Therefore, the error tracking is serious problem.

This paper proposes the detection scheme of error tracking. The proposed detection scheme utilizes the spatial correlation among sensing results. In the proposed detection, there are two periods, learning and detection periods. In learning period, the special correlation is evaluated from the perfect separated results. It is a supervised learning. In detection period, the comparison of special correlations between the learning period and the detection one is evaluated. If the special correlation in detection period is different from that in the learning one, the FC can recognize the error tracking. We evaluate the accuracy of error tracking by computer simulation.

II. OVERVIEW OF PHYC-SN

Figure 1 shows an overview of PhyC-SN. The sensors access to a FC. Therefore, the network topology of considered WSN is star type.

For the modulation of PhyC-SN, the small frequency bands are obtained by the inverse fast Fourier transform (IFFT), where these are referred to as subcarriers. In PhyC-SN, the mapping table between the sensing result and the subcarrier number is constructed. Each sensor sent the subcarrier whose number is matched to the sensing result to FC in accordance with the constructed mapping table.

In the PhyC-SN, all the sensors simultaneously access to FC. FC can detect the frequency spectrum of received signal by fast Fourier transform (FFT). As a result, it can detect subcarrier component. Since the detected subcarrier number is matched to the value of sensing result, the FC can recognize each sensing data. If the sensing results are widely spread,

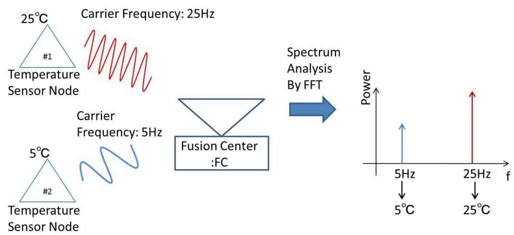

Fig. 1. Overview of PhyC-SN

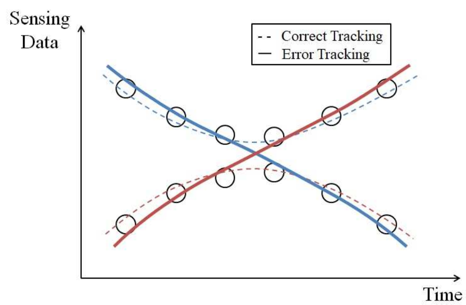

Fig. 2. Image of Error Tracking

FC can recognize the mean value and the deviation of all the sensing results. Therefore, PhyC-SN can achieve the bundle reception of all the sensing results.

The PhyC-SN, however, cannot detect each sensing data, separately. We proposed the data separation technique based on data tracking technique [4]. If the some data are near together, the proposed data separation technique fails. Once some data are recognized as the different separated sensing data, the proposed technique tracks the wrong sensing data. This kind of failure is error tracking. Figure 2 shows the image of error tracking. Therefore, the error tracking causes the serious error recognition.

III. Proposed Detection of Error Tracking

The proposed detection of error tracking is composed of two periods, learning period and detection period. In the learning period, the special correlations among sensing results are evaluated during under the perfect data separation. Therefore, our proposed technique is categorized as the supervised learning. The value of special correlations are averaged during the certain time period. In detection period, the special correlation among sensing results are also evaluated and then the comparison between the evaluated special correlation and that in learning period is performed. If the difference between them is larger than the certain threshold, the FC decides that the error tracking occurs.

The special correlation among sensing results is evaluated by the following equations.

$$\rho_{xy} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^2}\times\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\overline{y})^2}} \quad (1)$$

where x_i and y_i are the sensing results of x and y sensor nodes, respectively, n is the averaging period, and $\bar{x}$ and $\bar{y}$ are the averaging value of sensing results of x and y sensor nodes, respectively.

IV. Numerical Results

A. Random Model for Sensing Results

Firstly, we evaluate an accuracy of detecting error tracking by our proposed technique for the model of sensing results.

Table I shows the simulation parameters. For simple evaluation, an minimum square Euclid distance is utilized as the criterion for the data separation technique [5]. In learning period, we assume that data separation is ideally successful, where $\rho_{inf,i,j}$ is the special correlation of sensing results between ith sensor and jth sensor.

After learning period, in detection period, the time duration when the error tracking occurs is specified. After that, the two special correlations are evaluated under error tracking and under the perfect modification to error tracking, respectively. The former and the latter of correlation values are $\rho_{false,i,j}$ and $\rho_{true,i,j}$, respectively.

Since there are three sensors, the number of correlation values are three. We define the following two differences between the correlation value in detection period and that in learning period.

$$\Delta\rho_{n.true.ij} = ||\rho_{inf.ij} - \rho_{n.true.ij}||_2 \quad (2)$$

$$\Delta\rho_{n.false.ij} = ||\rho_{inf.ij} - \rho_{n.false.ij}||_2 \quad (3)$$

If $\Delta\rho_{n,true}$ is smaller as well as $\Delta\rho_{n,false}$ is larger, the sensitivity of detecting error tracking is higher. In other words, the larger the difference between $\Delta\rho_{n,true}$ and $\Delta\rho_{n,false}$ is, the higher the sensitivity of detecting error tracking is.

The random models of sensing results with special correlation and with time correlation are generated by Ref. [6]. For generating the random sensing results, we perform the following steps. First, we get the random value of sensing result with special correlation. After this, for obtaining the random value in the next time, the random value of sensing result with time correlation is obtained. After this, the random value with special correlation is obtained, again. Therefore, the random values with time correlation and special one are alternately obtained.

We assume the generated random values are considered as sensing results. Table I shows the parameters of random sensing results in each sensor.

The special correlation among three sensor are given as follow.

$$R = \begin{pmatrix} 1.00 & 0.60 & 0.20 \\ 0.60 & 1.00 & 0.10 \\ 0.20 & 0.10 & 1.00 \end{pmatrix} \quad (4)$$

$$\rho = 0.90 \quad (5)$$

TABLE I
MODEL OF RANDOM SENSING RESULTS

	Node1	Node2	Node3
mean value	1.20	1.76	2.99
standard deviation	0.29	0.34	0.40

TABLE II
SIMULATION PARAMETERS

Number of Trials	1000
Number of Node	3
Number of Sample	50,100,300,500,1000

B. Comparison of Correlation Values

Table II shows the simulation parameters. For considering the detection of error tracking, the following hypothesis test is assumed.

$$H_0 : \text{Error Tracking Occurs}$$

$$H_1 : \text{Error Tracking does not Occur}$$

If H_0 is true but the detector of error tracking decides that H_1 is true, this event is defined as false alarm. If H_1 is true but the detector decides that H_0 is true, this event is defined as miss detection. The probabilities of false alarm and miss detection are P_{FA} and P_M, respectively.

C. Simulation Results

Figures 3 and 4 show the performance between cumulative distribution function (CDF) and the differences between the true correlation and the correlation evaluated in learning period and the false correlation, where these differences are given by eq. (2) and eq. (3). The time durations for evaluating correlation value are 100 in Fig. 3 and 500 in Fig. 4, respectively. As we can see, the difference of false correlation is farer than that of true correlation as the time durations for evaluating correlation becomes larger. Therefore, the sensitivity of detecting error tracking becomes higher owing to enlarging the time duration for averaging the correlation.

In accordance with the result of CDF performance, we consider hypothesis test. We set the certain threshold for deciding the error tracking occurs or not. If the certain threshold is larger than the difference of correlation values in learning period and in detection period, FC decides the error tracking occurs and otherwise it decides the error tracking does not.

Figure 5 shows the result of hypothesis test. In this figure, the vertical axis and the horizontal one are the probabilities of false alarm and miss detection, respectively. From this figure, for the miss detection and the false alarm under 10 %, the required time duration for evaluating correlation should be larger than 500.

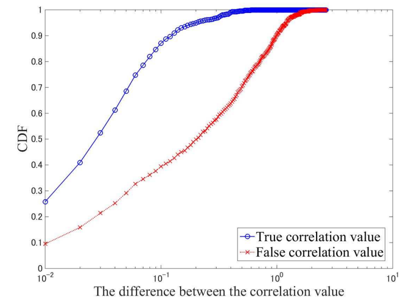

Fig. 3. CDF of Difference of Correlation in learning period and in detection period in 100 time duration for averaging

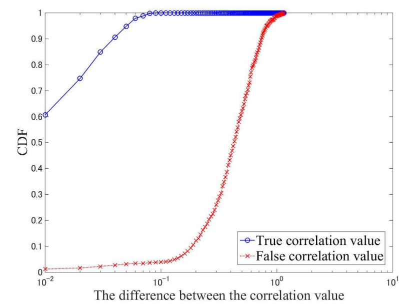

Fig. 4. CDF of Difference of Correlation in learning period and in detection period in 500 time duration for averaging

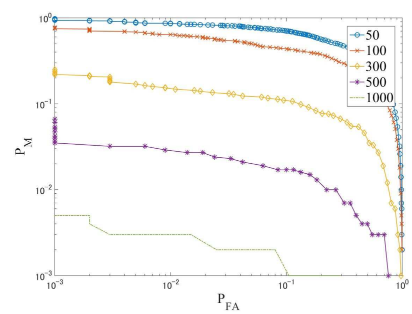

Fig. 5. Performance of Probabilities between False Alarm and Miss Detection

V. EXPERIMENTAL RESULTS

A. Measurement Environment

We use five temperature sensors within the indoor room. Figure 6 shows the appearance of measurement environment. Five sensors are put on the common altitude. The measurement period of temperature sensor is one minute. Five temperature sensors are worked during 3 days. Figure 7 shows the measurement results. For evaluating the detection accuracy of error tracking, we select three results of temperature sensors, which are Node 1, 2, and 5.

B. Accuracy of Detecting Error Tracking

We explain how to perform the evaluation of accuracy of detecting error tracking. The measurement results are separated into the results of two days and those of the left one day. The former and the latter are considered as the learning

Fig. 6. Appearance of Measurement Environment

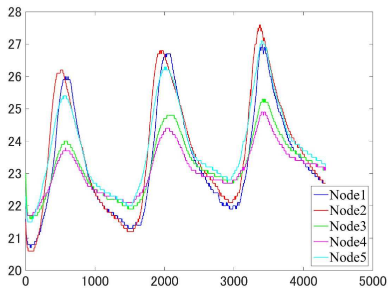

Fig. 7. Measurement Results of Temperature Sensors

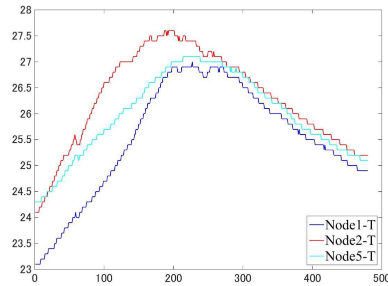

Fig. 8. Grand Truth of Separation Results

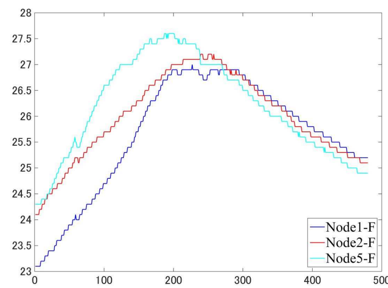

Fig. 9. Separation Results with Error Tracking

period and the detection period in our proposed detection. In learning period, the time correlation among sensing results is evaluated in the same manner as computer simulation. In detection period, the data separation with data tracking is performed for specifying each sensing result, where we use the minimum Euclid distance as the criterion of data tracking. As a result, error tracking occurs in some time durations. We got the false correlation in the duration with error tracking and the true correlation in the same period after modifying the error tracking.

Figures 8 and 9 show the grand truth and the separation result, respectively. In accordance of two results, we confirm the error tracking occurs.

C. Evaluation Results

Table III shows the results of three correlation values. These are the correlation value evaluated in learning period, the correlation value without error tracking, and that with error tracking, respectively. From this table, the differences of correlation value between Node 1 and Node 2 and Node 1 and Node 5 are so large that the detector can recognize the error tracking. However, in Nodes 2 and 5, the difference between the correlation value evaluated in learning period and that without error tracking is larger than between that and the correlation value with error tracking. The miss detection occurs from this results. For avoiding miss detection, we have to select the suitable correlation value for detecting the error tracking.

TABLE III
CORRELATION VALUE IN LEARNING PERIOD AND DETECTION ONE

	Node1,2	Node1,5	Node2,5
Correlation value in the learning section	0.7181	0.9626	0.8673
Correlation value in correct data	0.8408	0.9579	0.9326
Correlation value in erroneous data	0.9215	0.6978	0.8885

VI. CONCLUSIONS

This paper proposed the detection scheme for error tracking in the data separation results of PhyC-SN. We assume the special correlations among sensing results are statistic. If error tracking occurs, these are changed. In the proposed technique, the correlation value among sensing results is evaluated in supervising manner and that the comparison between the learned correlation and the detected one is performed for detecting error tracking. In the computer simulation and the experimental evaluation, the accuracy of detection for error tracking is evaluated. It is important future works to find the suitable sensor for detecting error tracking.

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