A Signal Separation Method for Physical Wireless Parameter Conversion Sensor Networks Using K-Shortest Path

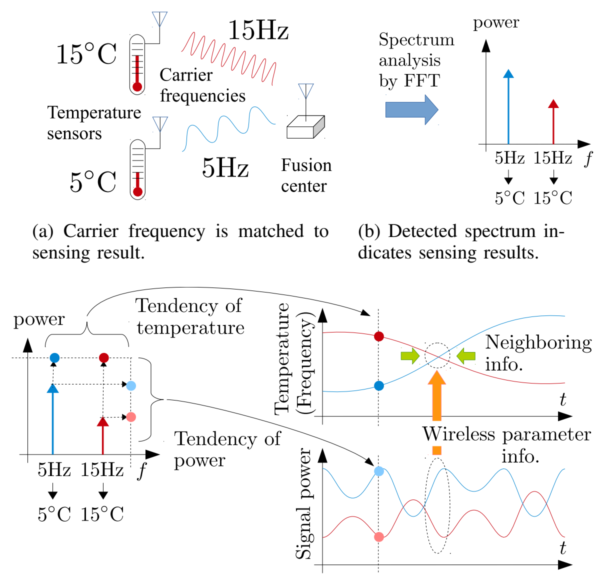
Shuhei Yamasaki* Minato Oriuchi* Osamu Takyu* Keiichiro Shirai*
Takeo Fujii† Mai Ohta‡ Fumihito Sasamori* Shiro Handa*
* Shinshu University, Nagano, Japan
E-mail: takyu@shinshu-u.ac.jp Tel/Fax: +81-26-269-5255
† Northwestern The Univ. of Electro-Communs., Tokyo, Japan
‡Northwestern Fukuoka University, Fukuoka, Japan

***Abstract*—Addressing low delay and high traffic performance is a technique necessary for wireless sensor networks (WSN). Although physical wireless parameter conversion sensor networks (PhyC-SN) achieve simultaneous information gathering from multiple sensors, separating the gathered mixed sensing results becomes a difficult problem. The proposed method utilizes an approach used in multi target tracking (MTT) in order to separate the mixed data points into a set of sequential ones. Particularly, we regard the data separation problem as path planning problems. In short, we consider paths by connecting data points observed at the adjacent time, and find a set of continuous paths consisting of data points of the same sensor. Following the problem, the same number of paths as sensors are obtained, so all sensing results can be correctly discriminated and labeled over all times in WSN. Therefore, we focus on a k-shortest pass method of MTT. In this paper, we show the accuracy of signal separation through simulation experiments and evaluate it in terms of the precision rate quantitatively.**

I. Introduction

As represented by *machine to machin* (M2M) communications and *internet of things* (IoT), by utilizing *wireless sensor networks* (WSN) and gathering sensing results that show various conditions of objects and persons, novel applications such as biological monitoring of animals and automatic driving of vehicles have been developed [1], so the WSN are rapidly gaining attention. As techniques necessary for WSN, although addressing low delay and high traffic requirements is important [2], the current WSN cannot be applied flexibly to various requirements. The one reason comes from packet communications. When multiple sensors coincidentally access to a server, packet loss will occur because of packet collision, so the server cannot gather sensing results from the sensors simultaneously.

To address this problem, *physical wireless parameter conversion sensor networks* (PhyC-SN) has been proposed in [3]. The method sends information while switching wireless parameters, *i.e.*, frequency, phase, and duration of a carrier, depending on sensing results. As shown in Fig. 1, when some sensors coincidently send information to the *fusion center* (FC), the FC can discriminate the parameters of each carrier by using spectrum detection and signal analysis, and can



(a) Carrier frequency is matched to sensing result.
(b) Detected spectrum indicates sensing results.
(c) Sequence separation is performed by using two information.

Fig. 1. The operation principle of PhyC-SN.

recognize sensing information of all sensors simultaneously. Furthermore, in addition to obtaining real time processing, in the case of high traffic, it can avoid packet collision compared to packet communications such as a ZigBee, so it achieves high throughput performance [4]. However, in the PhyC-SN, statistics of sensing results such as median and variation can be discriminated by using a clustering method, while sources of each result (data point) cannot be identified [3]. When an FC continuously receives data for a specific time, results informed from each sensor become time series like a curve, but they are superimposed and consists of curves having some cross points.

The purpose of this paper is separating the observed superimposed curves consisting of sensing data points into each curve obtained from the same sensor, and labeling the same sensor index to the set of data points. To address this problem, the authors of this paper first employed an approach based on data tracking [5], *i.e.*, the method tracks a sequential data points (scalar values) by Kalman filtering to predict and track the time-series variations of data point positions. The Kalman filter, however, cannot follow data points with steep variations, so it is prone to wrongly track data points.

To improve the accuracy of data tracking, the authors have considered the state probability of other information (data point with vectorial values), and extended the tracking method to a *multi target tracking* (MTT) method [6], [7]. The methods achieve high accuracy data separation by adding the signal power of each sensor as a unique sub information, and using a *graph cuts* method [8], [9] to segment mixed data points into a sequential ones and label them a unique label. The graph cuts, however, cannot constraint the number of assigned labels (tracking objects) per time to one, and this wrong labeling (tracking) causes time periods when sensors are not correctly recognized as shown in Fig. 5(b), (c), and (d).

In this paper, we regard the aforementioned problem as *path planning problems* to find a set of continuity paths consisting of sequential data points, and focus on a *k-shortest path* method [10]. Note that our previous method using the graph cuts, actually, regards the problem as *region segmentation problems*. In the proposed method, we think paths connecting data points of adjacent times, and find k shortest paths in which the sum of Euclidean distances between adjacent data points (vectorial values) are minimized. Using this approach, a unique path (label) is assigned to a data point per time.

We apply the k-shortest path method to the PhyC-SN, and quantitatively evaluate the accuracy of signal separation in terms of the precision rate. Through the evaluations of simulation experiments, we show that the proposed method outperforms the previous methods, and it can keep the discrimination accuracy in various wireless communication environments.

II. The operation principle of PhyC-SN

Figure 1 shows the overview of the PhyC-SN that our study focuses on. The network topology is a star type one in which multiple sensors send information to one fusion center (FC).

In the wireless equipment of each sensor, 0-1 indicator signals of length N is prepared as the input of inverse fast Fourier transformation (inverse FFT), and a 1 is set to the n-th point, while 0 is set to the other points, where the index $n \in [0, N-1]$ is called *indicator*. The indicator is converted depending on sensing results using a user defined rule, *e.g.*, in the case of temperature sensors, 23.4°C is expressed as $n = 234$.

The IFFTed output is sent to an FC as a sine wave, while the FC receives multiple waves sent from all the sensor nodes. Then, the set of received superimposed waves is FFTed and spectrum detection is applied to the restored indicator signals to find positions with high values since each of them corresponds to a sensing scalar value. As the result, the simultaneous information using multiple sensors become possible.

This method is, however, sensitive to frequency offset arising in transmitter and receiver. In such a case, transmitted data is falsely discriminated, and the orthogonality of carrier frequencies is corrupted, so inter-carrier interference causes virtual image information. Therefore, some frequency compensation methods have been proposed [11], [5]: a frequency compensation method using reference signals from the FC [11]; a fractional frequency offset compensation method using multiple receiver antennas [5]. In this paper, we assume that the countermeasure against the frequency offset is sufficiently effective, so ignore the influence by the offset.

III. Our approach for data separation in PhyC-SN considering multi target tracking [6], [7]

The purpose of this paper has been described in the introduction, and this kind of problem is discussed in the field of images recognition such as *region segmentation* and *multi target tracking*, so we have considered approaches based on them. This section first describes notation of data points and graph composed by connecting the adjacent points, and then describes our conventional method and its problem [6], [7].

Figure 2 shows a simple example of a graph composed by data points (nodes) and paths (edges) used in our methods. The indexes of a target node and its adjacent node (in time space) are, respectively, denoted as i and j, where actually $j^{(t+1)} \in \mathcal{N}(i^{(t)})$, t denotes a time, $\mathcal{N}(i)$ denotes a set of neighboring nodes in time space. Each node has vectorial sensing values, *e.g.*, time t_i, temperature (Celsius) c_i, humidity h_i, electric power p_i, and *etc.*. Then, connecting the adjacent nodes by edges, we obtain the graph. Here, the sets of all nodes and edges are, respectively, denoted as $\mathcal{V} := \{i\}$ and $\mathcal{E} := \{i, j\}$ Using these node and connection information, we guess the label x_i of a node, *i.e.,* decides which sensor gives the data point.

In our conventional method, we try to directory obtain the label of each data point by using *graph cuts* (GC) algorithm. The algorithm is used for finding the label of a node so that adjacent nodes have the same label and they construct a segment (set of sequential nodes having the same label). The label is guessed using information of nodes (aforementioned vectorial values) and labels of adjacent nodes. In formulation, the node information is expressed by a data fidelity function (also called a unary term in GC) $U_i(x_i)$, where x_i is a label to be solved, while the adjacent information is expressed by a smooth function (a pairwise term in GC) $P_{i,j}(x_i, x_j)$. The problem and each term are expressed as the following

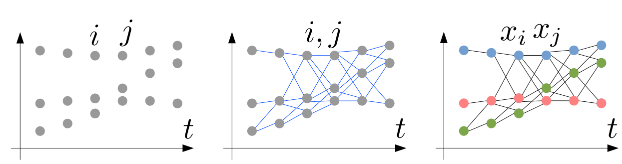


Fig. 2. An simple example of a graph composed by data points (nodes) and their connections (edges).

minimization problem:

$$\min_{\{x_i\}} \sum_{i\in\mathcal{V}} U_i(x_i) + \lambda \sum_{(i,j)\in\mathcal{E}} P_{i,j}(x_i, x_j), \quad (1)$$

where λ is a balancing weight.

The unary term is a cost function and we expressed it by using a feature based on wireless parameters in [6], [7]. As shown in the later Fig. 4(b), in the WSN based on physical wireless parameter conversion, each sensor sends the signal through a unique wireless channel, so fading and propagation loss give different signal amplitude (received signal power) and phase information by sensors. Additionally, since the wireless communication environment of WSN is usually static, the fading correlation in the time domain is high. Therefore, we focused on the received signal power of each sensor. Since instantaneous values obtained from the same sensor are thought to be similar to each other, we expressed the unary term so as to minimize the difference between instantaneous value p_i and average value of a sensor μ_{x_i} (given as a known value):

$$U(x_i) := (p_i - \mu_{x_i})^2, \quad (2)$$

where the squared difference, *i.e.*, ℓ_2 norm, is used for simplicity. Note that the unary term can be modeled with the phase component of fading in addition to the amplitude component. The extended dimension of the unary cost can improve the tracking accuracy.

The pairwise term is also a cost function, we expressed it by using a sensing value, *e.g.*, Celsius temperature c_i in [6], [7]. Since the information sent from the same sensor has time continuity and similar values, the difference is thought to become small:

$$P(x_i, x_j) := |c_i - c_j|, \quad (3)$$

where the absolute difference, *i.e.*, ℓ_1 norm, is used in order to reduce the influence by outliers.

Using the (1)$\sim$(3), the conventional methods examined two types of cost functions, one uses only a temperature value, and the other uses temperature and received signal power. The cost function using a temperature value cannot separate similar sensing results observed around cross point of curves, especially near parallel overlapped curves. On the other hand, by adding a received signal power, the cost function can separate sensing results. In this way, using the feature of wireless parameters in addition to sensing results, we can increase the feature dimension to discriminate the sensing results, *i.e.*, when some sensing values or features become similar, the other ones can be used for the separation.

As a solution to solve this kind of labeling problems (linear integer programming problem), the aforementioned conventional methods use *belief propagation* [12], [13], [14] and the GC [8], [9]. Their effectiveness has been shown in many applications especially in computer vision. However, the formulation for these algorithms cannot deal with the constraint not to assign the same label to some sensors. As a result, the label duplication, which some sensing results at a same time are assigned to common label, easily occurs.

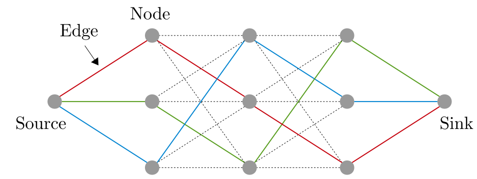


Fig. 3. A simple example of k-shortest path ($k = 3$).

IV. Proposed Method Based on k-Shortest Path

The purpose of the k-shortest path method is to find k unbranched paths passing edges of a directed graph connecting nodes from the source node to the sink node, and minimize total costs required for passing edges. Note that the method is different from a method that removes the shortest pass one after another, and consequently finds k paths.

Figure 3 shows an example of a small size $k = 3$ shortest pass. The nodes are data points given by three sensors, and the edges (dotted lines) are obtained by connecting the adjacent nodes. A different passing cost is randomly set to each edge. Here, the obtained three paths do not share the same node, so the label of each node can be determined uniquely by following each obtained path and adding a label to passing nodes.

In the formulation of this method, edges are determined to be used or not to be as binary states, and used edges are constrained so as to be a continuous unbranched path. Consider a edge connecting $i^{(t)}$ and $j^{(t+1)}$, and the passing cost $y_{i,j}$ (≥ 0) (described later). Then, introduce a variable to be solved $b_{i,j} \in [0, 1]$ (continuous real value within the range from 0 to 1) as the usage rate of this edge, where 0 and 1 indicate not used and used, respectively. Although this is a relaxation problem of the 0-1 binary programming to solve $\{0, 1\}$, it gives sufficient accuracy.

Using the introduced variables, the total cost of k paths can be expressed as follows, and its minimization is considered:

$$\min_{\{b_i\}\in[0,1]} \sum_{i,j\in\mathcal{E}} y_{i,j} b_{i,j}, \quad (4)$$

where we define the passing cost $y_{i,j}$ by using sensing values, *e.g.*, temperature values c_i and c_j in this paper, and using wireless parameters, *e.g.*, received signal power values p_i and p_j as

$$y_{i,j} := \sqrt{|t - (t+1)|^2 + w_c|c_i - c_j|^2 + w_p|p_i - p_j|^2}, \quad (5)$$

where the balancing weights for each term are set to $w_c = 43.1$, and $w_p = 139.2$ in the experiment, and determined so that the variances of the differences become equal to each other.

Generating a path by concatenating edges requires the following two constraints:

(i) If a path uses a node i, one of the edges between the node and adjacent nodes on the starting point side $k^{(t-1)} : i^{(t)} \in \mathcal{N}(k^{(t-1)})$ is used. So is the end point side $j^{(t+1)} \in \mathcal{N}(i^{(t)})$.

(ii) k of the edges connecting to the starting point (source) v_{source} are used. So is the end point (sink) v_{sink}. These constraints are practically defined as follows:

$$\begin{aligned} \text{s.t.} \quad & \forall_i \sum_{j \in \mathcal{N}(i)} b_{i,j} \leq 1 \\ & \forall_i \sum_{j \in \mathcal{N}(i)} b_{i,j} = \sum_{k: i \in \mathcal{N}(k)} b_{k,i} \\ & \sum_{j \in \mathcal{N}(v_{\text{source}})} b_{v_{\text{source}},j} = \sum_{k: v_{\text{sink}} \in \mathcal{N}(k)} b_{k,v_{\text{sink}}} \end{aligned} \tag{6}$$

The problem formulated as the above is a linear programming (LP) problem dealing with real continuous values, and it can be solved by using general LP solvers such as CPLEX, Gurobi, and MATLAB's optimization toolbox. Although the original 0-1 binary programming problem to obtain $\{0, 1\}$ values are relaxed as continuous problem to obtain $[0, 1]$ values, almost the same results as the binary problem are obtained, as is described in the original paper of the k-shortest path [10].

V. Simulation experiments

This section shows comparisons and evaluations of conventional method [7] and proposed method as for qualitative evaluation, quantitative evaluation, and evaluation under various wireless environments.

A. Preparation and setting

This section shows comparisons and evaluations of conventional method [7] and proposed method as for qualitative evaluation, quantitative evaluation, and evaluation under various wireless environments.

B. Preparation and setting

Using five temperature sensors placed in a room, we measured 600 data points for 10 minutes at 1 second intervals, and use the temperature values saved on a sensor as an information source of WSN in the computer simulation. As for the details of the measurement environment, see [5]. The parameters of the wireless communication system are shown in Table I.

Figure 4(a) shows sensing results of each sensor, and (b) shows received signal power when sending the information bearing signal by PhyC-SN. The channel between each sensor and FC is modeled by independent Rice fading, where Rice factor is defined by R. The path loss in nth sensor ($n \in 0, 1, \ldots, 4$) is modeled by nP (dB). For example, $P = 0$ dB, the average received power of the signals accessed by all the sensors is equal. If $P = 2$ dB, the average received power of the signal accessed by nth sensor is $2n$ dB smaller than that accessed by 0th sensor. In sections V-C and V-D, $(R, P) =$(0dB, 0dB). In section V-E, $(R, P) =$(0 dB, 0 dB), (3 dB, 3 dB) and (5 dB, 5 dB).

C. Qualitative evaluation

Figure 5 shows the labeling results of the previous method [7] (b)∼(d) and the proposed method (e). From the results of the conventional method, one can see that wrong continuous paths appear frequently around cross points. This is because the costs around the cross points become unclear. On the other hand, the proposed method successfully tracks the data points (e), and almost the same result as the ground truth (f) is obtained. This is because each of temperature and electric power supports the separation of the other.

D. Quantitative evaluation

As a quantitative evaluation, we use *precision* rate, which is a measure to show the rate of correct results included in the all results, defined as

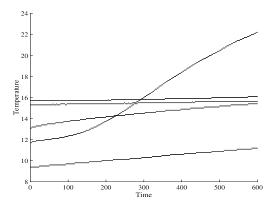
$$\text{precision} := \frac{|\{\text{successfully tracked sensing results}\}|}{|\{\text{all sensing results}\}|}, \tag{7}$$

where $|\{\cdot\}|$ denotes the number of elements in a set. High precisions show high separation accuracy.

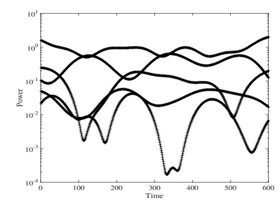
Figure 7 shows the precisions of the aforementioned results shown in Fig. 5. We also show data separation results corresponding to representative precisions 90%, 95%, 98% in Fig. 6. In Fig. 7, the proposed method outperforms the conventional method, and includes few wrong discrimination. When using the temperature and electric power, the proposed method achieves 99%, which is 10% higher than

TABLE I
Preparation and setting for simulation experiments.

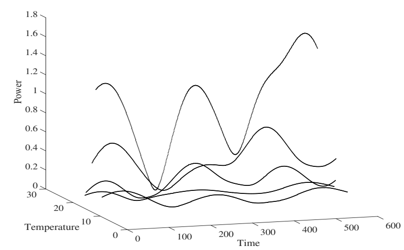
Type of Sensor	Temperature Sensor
Observation Time	600 (s)
FFT Points	512
Possible Observation Area	0 to 51.2 (deg.)
Resolution of Sensing Results	0.1 (deg.)
Number of Sensor	5
Fading Model	Independent Rice Fading for Each User
Rice Factor R	$0, 3, 5$ (dB)
Normalized Doppler Frequency	0.005
Average Power of Each Sensor P	$0, 3, 5$ (dB)



(a) Temperature

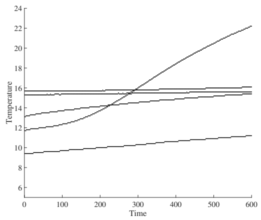


(b) Electric power

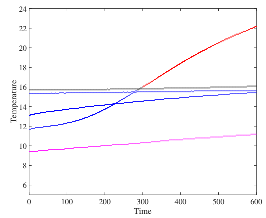


(c) 3D plots of temperature and electric power

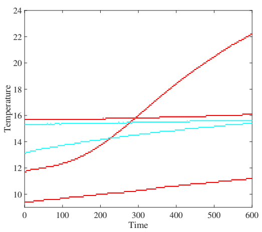
Fig. 4. Detected superimposed signals of temperature (a), electric power (b), and multidimensional expression of them.



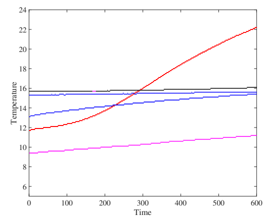
(a) Original



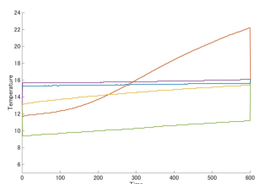
(b) [6] (temp.)



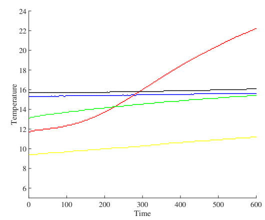
(c) [6] (power)



(d) [6] (temp.+power)

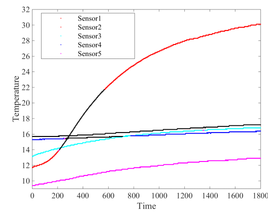


(e) Prop. (temp.+power)

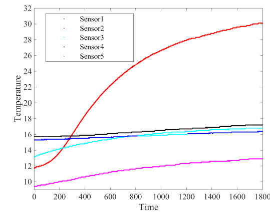


(f) Ground truth

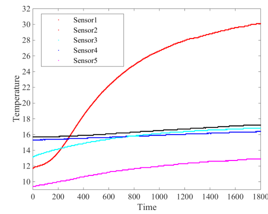
Fig. 5. Data separation results of conventional method [6] and proposed method. Unseparated superimposed data (a). The conventional method using temperature (b), electric power (b), and both of them (c). The proposed method using temperature and electric power (e). Ground truth (f).



(a) Precision 90%



(b) Precision 95%



(c) Precision 98%

Fig. 6. Data separation results corresponding to precision rates.

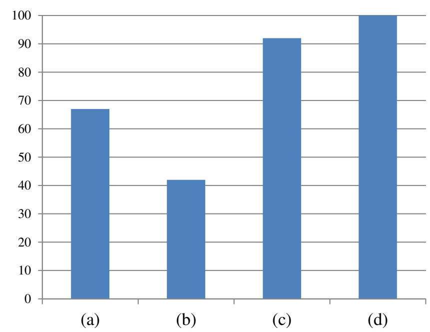


Fig. 7. The precisions of conventional method [6] and proposed method. The conventional method using temperature cost (a), electric power cost (b), and both costs (c). The proposed method using both costs (d).

the conventional method with 91%. In Fig. 6, comparing the results corresponding to precisions, one can see that wrong discrimination occurs in the precision 91%, while the precision 98%, which is given by the proposed method, is almost completely separated.

E. Evaluation in various environments

We evaluate precisions of the proposed method in a case using noisy signals and different parameters of the wireless environment. Figure 8 shows results when using noisy temperature values added uniform random numbers from 0 to 0.5 deg. Steep variations are recognized as information fluctuation. We model the noise as uniform random variable from 0 to x deg., where $x \in \{0.1, 0.3, 0.5\}$.

Figure 9 shows the precisions of the proposed method using various noisy signals obtained by changing the aforementioned parameters. In the figure, the increase of the maximum noise x is related to the decrease of precisions. However, the precisions improve by increasing the propagation loss P and Rice factor R. It is due to the following reason. As P and R increase, the probability that signals of each node takes the same signal power decreases, and the uniqueness of each node in signal power increases, so the accuracy of data separation is improved.

VI. Conclusions

In this paper, we have focused on the k-shortest path method for improving the performance in the data separation of the PhyC-SN, and evaluated the accuracy in terms of the precision rate quantitatively. The evaluation of computer simulations showed that the proposed method achieves high accuracy discrimination compared to the conventional methods, and can keep the accuracy under various wireless environments. The drastic improvement in the precision rate comes from that the proposed method can avoid assigning duplicate labels at the same time, and also it performs the data separation using multiple features such as temperature and received signal power. As future work, we currently try to deal with the data points as a group, *i.e.*, small line segment (called a “tracklet” in MTT), and utilize the feature of tracklets for further improving the accuracy.

Acknowledgment

A part of this research project is sponsored by *ministry of internal affairs and communications* in Japan under the

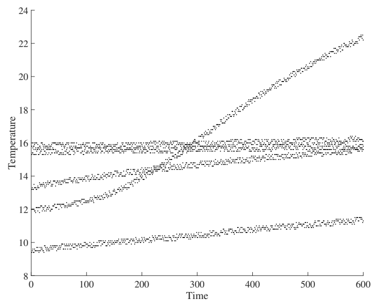


Fig. 8. Sensor information with additive noise modeled as uniform random numbers from 0 to 0.5 deg.

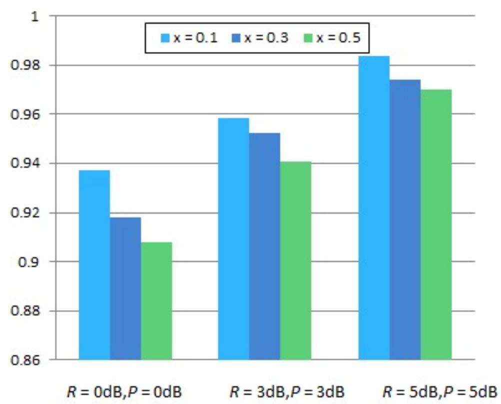


Fig. 9. The comparison of precision rates when sensing results with additive noise are informed under various wireless environment.

project name of *strategic information and communications R&D promotion programme* (SCOPE 175104004).

REFERENCES

[1] Y. Gao, Z. Qin, Z. Feng, Q. Zhang, O. Holland, and M. Dohler, "Scalable and reliable IoT enabled by dynamic spectrum management for M2M in LTE-A," IEEE Internet of Things Journal, vol. 3, no. 6, pp. 11351145, 2016.

[2] C. Lu, A. Saifullah, B. Li, M. Sha, H. Gonzalez, D. Gunatilaka, C. Wu, L. Nie, and Y. Chen, "Real-time wireless sensor-actuator networks for industrial cyber-physical systems," Proceedings of the IEEE, vol. 104, no. 5, pp. 10131024, 2016.

[3] T. Endo and T. Fujii, "Real time information gathering based on frequency and timing assignment for wireless sensor networks," in IEEE Int. Conf. on Commun. Sys. (ICCS), 2012, pp. 167171.

[4] K. Kakinuma and T. Fujii, "Multiple information collection by utilizing physical wireless parameter conversion sensor network," in Int. Conf. on Info. Network. (ICOIN), 2017, pp. 377382.

[5] R. Myoenzono, O. Takyu, K. Shirai, T. Fujii, M. Ohta, F. Sasamori, and S. Handa, "Data tracking and effect of frequency offset to simultaneous collecting method for wireless sensor networks," Int. J. Distributed Sensor Networks, vol. 2015, pp. 110, 2015.

[6] M. Oriuchi, O. Takyu, K. Shirai, T. Fujii, M. Ohta, F. Sasamori, and S. Handa, "Multi-target tracking based on features of sensing results and wireless parameters for physical wireless parameter conversion sensor networks," in IEEE Radio and Wireless Symp. (RWS), 2016, pp. 230 233.

[7] M. Oriuchi, O. Takyu, K. Shirai, F. Sasamori, S. Handa, T. Fujii, and M. Ohta, "Performance evaluation of multi-target tracking for PhyC-SN," in IEEE Wireless Commun. and Network. Conf. Workshops (WCNCW), 2016, pp. 351354.

[8] Y. Boykov and V. Kolmogorov, "An experimental comparison of mincut/ max-flow algorithms for energy minimization in vision," IEEE Trans.on Pattern Anal. and Machine Intelli. (PAMI), vol. 26, no. 9, pp. 1124 1137, 2004.

[9] Y. Boykov and O. Veksler, Handbook of Math. Models in Comput. Vis. Springer, 2006, ch. Graph cuts in vision and graphics: theories and applications, pp. 7996.

[10] J. Berclaz, F. Fleuret, E. Turetken, and P. Fua, "Multiple object tracking using k-shortest paths optimization," IEEE Trans. on Pattern Anal. Machine Intelli. (PAMI), vol. 33, no. 9, pp. 18061819, 2011.

[11] B. Sklar, Digital communications: fundamentals and applications, 2nd ed. Prentice Hall, 2001.

[12] J. Pearl, Probabilistic reasoning in intelligent systems: networks of plausible inference. Morgan Kaufmann, 1988.

[13] Y. Weiss and W. T. Freeman, "Correctness of belief propagation in Gaussian graphical models of arbitrary topology," Neural Computation (Proc. of NIPS), vol. 13, no. 10, pp. 21732200, 2001.

[14] J. M. Mooij and H. J. Kappen, "Sufficient conditions for convergence of the sum-product algorithm," IEEE Trans. on Info. Theory, vol. 53, no. 12, pp. 44224437, 2007.