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# Energy-efficient Distributed Estimation Using Wireless Sensor with Wake-up Receivers

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***Abstract*—In this paper, we advocate applying the concept of wake–up radio to distributed estimation in wireless sensor networks. With distributed estimation, where sensing data of multiple nodes are used for estimating a target observation, the energy consumption can be reduced by making only a subset of nodes in the network transmit their data, such that the collected data can guarantee the required estimation accuracy. In this case, a sink needs to selectively wake up sensor nodes whose data can contribute to the improvement of estimation accuracy. In this paper, we propose a wake–up signaling called estimative sampling (ES) that can realize the selective wake–up of desired nodes. The ES method includes a mechanism that dynamically searches the desired nodes over a distribution of sensing data. With numerical results obtained by computer simulations, we show that the distributed estimation with ES method achieves lower energy consumption than that with conventional identity–based wake–up while satisfying the required accuracy.**

## I. Introduction

Wireless sensor networks (WSNs) play a key role in realizing many IoT–related solutions and applications [1]. One of the key requirements on IoT/sensor networks is energy efficiency since it directly affects the lifetime of IoT devices operating with limited amount of energy resource.

In order to achieve energy–efficient operations of sensor nodes, this paper focuses on wake–up radio, which reduces energy consumed by each node during a standby period [2]. We consider a scenario where sensor nodes are deployed around a sensing target, and a data collection node (called sink) requests these nodes to transmit their sensing data whenever needed. The sensor nodes are required to be in standby mode so that they can respond to the request from the sink. In order to reduce the energy consumed during this standby mode, an ultra low–power secondary radio called *wake–up receiver*, which is dedicated to wake–up signaling, is attached to each sensor node in addition to a main radio used for data transmissions. During standby mode, only the wake–up receiver is kept active while the main radio is completely switched off. When the sink requests data from sensor nodes, it first transmits a wake–up signal to trigger target nodes. The nodes with their wake–up receivers detecting the wake–up signal switch their main radios on, transmit their data, and transit back to standby mode. This operation can significantly reduce wasteful energy consumption, and has been shown to outperform conventional duty–cycling that is widely employed in standard protocols, such as IEEE 802.15.4e [3][4].

In this paper, we advocate applying the above concept of wake–up radio to *distributed estimation* in wireless sensor networks. With distributed estimation, multiple sensor nodes are deployed around a sensing target, and sensing data collected from these nodes are used for the estimation of a target observation [5][6]. The energy consumption of distributed estimation can be reduced by making only a subset of nodes in the network transmit their data, such that the collected data can guarantee the required estimation accuracy [7][8]. In this case, we need to appropriately choose the set of nodes which can contribute to the improvement of estimation accuracy. In this paper, we further attempt to reduce the energy consumption of sensor nodes by applying the wake–up receiver to each sensor node. Then, in addition to the selection of appropriate nodes, we need a mechanism for the sink to convey information on sensor nodes to be woken up to each wake–up receiver.

In this paper, we propose a wake–up signaling for distributed estimation called estimative sampling (ES), which enables a sink to activate only a subset of nodes whose data can contribute to the improvement of estimation accuracy. The proposed ES method is designed based on a wake–up control called content–based wake–up [9], which enables the sink to wake up target nodes according to the sensed data of each node. To the best of our knowledge, this is the first work to integrate the concept of wake–up radio with distributed estimation. The proposed ES method includes a mechanism that dynamically searches the desired nodes over a distribution of sensing data. With computer simulations, we show the efficiency of the proposed ES method in terms of energy–efficiency and data collection delay, which confirms that the proposed ES method well–controls the cross–layer interactions between information processing and PHY/MAC operations.

## II. System Model and wake-up signaling

### A. System Model

We consider a scenario of distributed estimation where $N$ sensor nodes are deployed around a sensing target to estimate a true observation of $\theta$ [5][6]. Due to the noise generated at each sensor node, the observed value $\theta_i$ of sensor node $i$ is expressed as

$$\theta_i = \theta + n_i, \tag{1}$$

where $n_i$ is assumed to be Gaussian with zero mean, i.e., $E[n_i] = 0$ and variance of $\sigma^2$. After the sink collects data from $n$ sensor nodes, the maximum-likelihood (ML) estimation can be calculated as the mean value of the collected data [5][6], i.e.,

$$\hat{\theta} = \frac{1}{n}\sum_{i=1}^{n}\theta_i. \tag{2}$$

The estimated value becomes more accurate with increased number of collected data. However, the more sensor nodes wake up and transmit data, the higher the total energy consumed by sensor nodes is. In this work, with the aim of reducing energy consumption, we consider a distributed estimation guaranteeing a certain required accuracy [7][8]. Thus, we attempt to collect data only from a subset of sensor nodes to achieve the required accuracy. We assume that the information on noise distribution, i.e., Gaussian, is known for the sink. On the other hand, the sink does not know its mean corresponding to the true value as well as the variance of $\sigma^2$. We also assume that sensed data are limited to $[V_{min}, V_{max}]$ due to dynamic range of each sensor. $V_{min}$ and $V_{max}$ are respectively assumed to be sufficiently smaller and larger than $\theta$ so that the probability to have noise causing $\theta_i$ to be smaller than $V_{min}$ and higher than $V_{max}$ is negligibly small.

We consider a scenario where a sink collects information observed by sensor nodes located within its communication range. We assume that each sensor node is equipped with a wake-up receiver, which detects wake-up signal (i.e., wake-up request) transmitted by the sink through non-coherent envelope detection and on-off keying (OOK) demodulation. This type of wake-up receiver has been shown to operate with ultra-low power consumption in the order of $\mu$W [2][3][4]. In standby mode, each sensor node switches off its main radio interface (I/F) to be used for data transmissions, and keeps only wake-up receiver active. After receiving a wake-up request from the sink through wake-up signaling, sensor nodes activate their main radio I/Fs, and immediately attempt to transmit sensing data with a signal packet based on CSMA/CA protocol defined in IEEE 802.15.4 [10]. When detecting a successful transmission of packet by receiving an ACK from the sink, each sensor node returns to standby mode. The sensor nodes, which succeeded in data transmissions, are controlled not to wake up for a certain period of time even if it receives a wake-up request from the sink. With these operations, the main radio I/F of each sensor node consumes energy only when needed, which can significantly improve energy-efficiency of WSNs [4][9].

### *B. Wake-up Signaling*

In this paper, we employ wake-up signaling that exploits the length of frame (i.e., the length of energy burst) transmitted by the main radio I/F at a sink [4]. The wake-up receiver at each sensor node detects the length of frame with non–coherent envelope detection and OOK demodulation, which is used to decide whether it should wake up or not. This wake-up signaling enables us to reuse the main radio I/F at the sink as a transmitter of wake-up signal, which avoids the installation of an extra hardware to transmit the wake-up signal into the sink. We consider two types of wake-up signaling: UCWu (Unicast wake-up) [2][9] and CoWu (Content-based wake-up) [9].

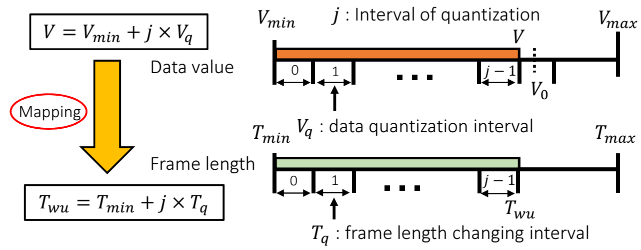


Fig. 1. Mechanism to decide wake-up frame length in CoWu.

*1) UCWu:* With UCWu, a unique wake-up ID is assigned to each sensor node, which is called unicast wake-up ID (UCWuID). A mapping between different wake-up IDs and different frame length is prepared in advance. When a wake-up receiver attached to a sensor node detects the frame length corresponding to its own wake-up ID, the sensor node wakes up. The advantage of UCWu is that no congestion occurs for data transmissions after the wake-up process because only a single sensor node wakes up. However, a problem is that the sink collects data based on IDs independent of the observed value of each sensor node. Therefore, it can not selectively collect data according to the observed value.

*2) CoWu:* CoWu is a wake-up signaling that controls target wake-up nodes based on the observed data of each sensor node [9]. With CoWu, a mapping between a range of value of sensing data and frame length is prepared in advance. Each sensor node sets the wake–up frame length (length to trigger wake–up process) into its wake-up receiver based on the observed value of sensing data. The sink transmits a wake-up signal with a frame length corresponding to a specific value of sensing data. For example, let us consider an example shown in Fig. 1, which shows a mapping between the range of observable data $[V_{min}, V_{max}]$ and that of frame length employed for wake-up control $[T_{min}, T_{max}]$. We define data quantization interval as $V_q$, and changing interval of frame length as $T_q$. Then, when the observed data $V_o$ belongs to $j$-th interval, its wake–up frame length $T_{wu}$ is set to $T_{wu} = T_{min} + j{\times}T_q$. For example, when a sink attempts to collect data above a certain threshold, a wake-up signal with the frame length corresponding to the target threshold is transmitted by the sink. By configuring nodes so that they wake up and transmit data if each wake–up receiver detects frame length larger than the specified threshold, we can realize wake–up of nodes owning data above a certain threshold. We call this type of CoWu as countdown CoWu (CD-CoWu). On the other hand, by making nodes detecting smaller frame length than the threshold wake up, we can realize countup CoWu (CU–CoWu) where nodes owning data below a certain threshold are activated. Although CoWu realizes content-based wake-up as described above, multiple nodes can wake up and transmit data simultaneously for a single wake-up request, which causes congestions among nodes.

## III. Proposed Estimative Sampling

In this paper, we propose a sampling method called estimative sampling (ES), which achieves energy-efficient estimation by exploiting the advantage of CoWu.

### A. Basic Operations of ES method

In ES method, a sink alternatively collects data from sensor nodes observing lower values and higher values by using CoWu, focusing on the fact that Gaussian distribution is line-symmetric with respect to the mean. In this section, we define $V^i_{low}$ as the $i$-th lowest observed data and $V^i_{high}$ as the $i$-th highest observed data. We define $n_c$ as the number of sensor nodes whose data have been collected by the sink. $n_c$ is composed of the number of sensor nodes with their data lower than the mean (denoted as $n_{low}$) and those with their data higher than the mean (denoted as $n_{high}$), i.e., $n_c$ = $n_{low}$ + $n_{high}$.

We describe the basic operations of ES method with Fig. 2, where data distribution between minimum ($V_{min}$) and maximum ($V_{max}$) is depicted. In order to collect data from a sensor node that observes $V^1_{low}$, wake-up trials are conducted from the lowest interval with CU-CoWu. The specified threshold is shifted with the step of $V_{step}$ ($V_{step} = n * V_q$, $1 \leq n \leq n_{max}$, where $n_{max}$ is the maximum number of quantization intervals) until any sensor node replies to a wake-up request. In this way, data can be first collected from sensor nodes that exist within the lowest data interval. Next, in order to collect data from a sensor node that observes $V^1_{high}$, CD–CoWu is conducted with the step of $V_{step}$ from $V_{max}$, which enables the sink to collect data from sensor nodes that exist within the highest data interval. If $n_{low} = n_{high}$, $\theta$ is estimated by using all collected data. On the other hand, if $n_{low} \neq n_{high}$, $n_{min}$ = $min(n_{low}$,$n_{high})$ is first obtained, and $\theta$ is estimated with $V^i_{low}$ ($i$∈{1,2,⋯,$n_{min}$}) and $V^i_{high}$($i$∈{1,2,⋯,$n_{min}$}). This is because the estimated value deviates from the true value if $n_{low}$ and $n_{high}$ are not balanced. In the example of Fig. 2, $V^1_{low}$ and $V^1_{high}$ are collected from the lowest and highest data interval. Then, since $n_{low} = n_{high}$, $\theta$ is calculated by using all collected data of sensor nodes. The sink can continue to shift data interval by $V_{step}$ from the lowest data interval, transmits the corresponding wake-up signal, and attempts to collect data from a sensor node that observes $V^2_{low}$.

The above-mentioned operation is repeated until the number of collected nodes reaches a pre-determined parameter of $n_r$, which is the required number of sensor nodes to achieve the desired estimation accuracy. Note that, when the sink finds the unbalanced number of $n_{low}$ and $n_{high}$, it attempts to collect data from the side with smaller number of nodes.

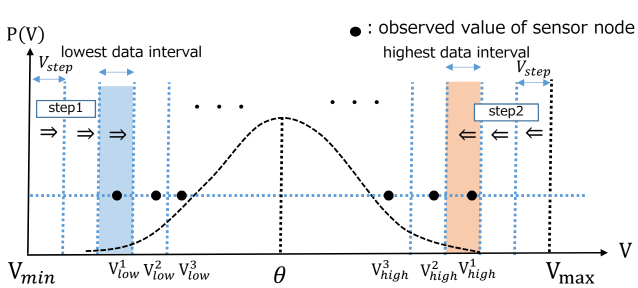


Fig. 2. Basic operations of ES method.

### B. Impact of $V_{step}$ on ES method

In terms of the energy efficiency, it is desirable that only a single sensor node exists in the specified range of ES method. This is because of possible congestion among activated nodes: if multiple sensor nodes simultaneously wake up and contend with CSMA/CA, there can be sensor nodes waiting for a long period of time with the operation of carrier-sensing and backoff process. Thus, by reducing the size of $V_{step}$, we can increase the probability that only a single sensor node exists in the specified range. However, a problem is that the mean and variance of Gaussian distribution are unknown for the sink, which makes it difficult to decide an appropriate value of $V_{step}$ based on the probability distribution. In this case, we need to set $V_{step}$ to the smallest possible value. However, reducing the size of $V_{step}$ increases the number of wake-up trials to be conducted until the sink finds the lowest and highest data interval, as a result, data collection delay increases. Therefore, we need a mechanism for the sink to set a sufficiently large interval so that data collection time can be shortened while offering low probability for multiple sensor nodes to simultaneously wake up. In this paper, we propose a method to dynamically set an appropriate interval that meets the above condition by using UCWu in addition to CoWu.

### C. Proposed ES method

In the proposed ES method, multiple modes of wake-up signaling are employed, which are switched by using a control signal transmitted by the sink. One mode is UCWu, and the other mode is CoWu classified into CD-CoWu mode and CU-CoWu mode. We prepare 3 control frame length to specify a mode to be adopted by wake-up receivers. When each wake-up receiver detects one of those length, it switches to the corresponding mode.

In the proposed ES method, data is first collected from one sensor node with a randomly–selected ID by adopting UCWu mode in order to get an idea on data range to be searched in the following CoWu mode. Specifically, from the value $V_U$ collected in UCWu mode, we prepare a truncated Gaussian distribution $G^i_{high}$ with a range of [$V_U$,$V^i_{HTh}$] and a truncated Gaussian distribution $G^i_{low}$ with a range of [$V^i_{LTh}$,$V_U$]. Here, $V^i_{HTh}$ and $V^i_{LTh}$ are the $i$-th highest and lowest threshold employed for CD–CoWu and CU–CoWu, respectively, where $V^0_{HTh}$ = $V_{max}$ and $V^0_{LTh}$ = $V_{min}$. Note that the mean and standard deviation of a truncated Gaussian distribution over a range of [x,y] are calculated as $\frac{x+y}{2}$ and $\frac{|y-x|}{5}$, respectively. Next, a threshold to search a node with the lowest or highest data with CoWu is determined such that the expected number of nodes observing data within the range of [$V^{i-1}_{LTh}$,$V^i_{LTh}$] or [$V^i_{HTh}$,$V^{i-1}_{HTh}$] is 1. For instance, $V^i_{LTh}$ is selected so that the probability that a node observes data in the range of

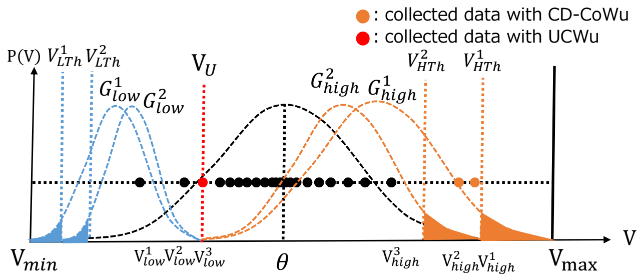


Fig. 3. Operations of ES method to collect $V^1_{low}$ or $V^1_{high}$.

$[V^{i-1}_{LTh}, V^i_{LTh}]$ expressed as

$$P = \int_{V^{i-1}_{LTh}}^{V^i_{LTh}} P_{G^i_{low}}(x)dx \tag{3}$$

becomes $\frac{1}{N}$, where $P_{G^i_{low}}(x)$ is probability density function (PDF) of $G^i_{low}$. The sink alternatively applies CU-CoWu and CD–CoWu with shifted thresholds to collect data from nodes belonging to the lowest and highest ranges. An example of $G^i_{low}$ and $G^i_{high}$ with shifted thresholds is shown in Fig. 3, where $V^1_{high}$ and $V^2_{high}$ are collected with 2nd trial of CD–CoWu.

After collecting either $V^1_{low}$ or $V^1_{high}$, $V_U$ in the above process can be replaced with the collected lowest or highest value. The sink tries to collect $V^1_{low}$ or $V^1_{high}$, which has not been collected with CU–CoWu or CD-CoWu. These operations are repeated until the sink collects a set of data including $V^1_{low}$ and $V^1_{high}$.

After both $V^1_{low}$ and $V^1_{high}$ are collected with the above operations, a truncated Gaussian distribution $\hat{G}$ with the range of $[V^1_{low}, V^1_{high}]$ is created. Then, the sink continues to collect data so that $n_{low}$ and $n_{high}$ become the same number. For instance, if $n_{low} \leq n_{high}$, it is desired to collect $V^{n_{low}+1}_{low}$. Here, the collected values are used to estimate the mean and variance of $\hat{G}$ [1]. That is, with the increased number of collected data, the estimation of $\hat{G}$ becomes more accurate. With $\hat{G}$, a new threshold is decided so that the expected number of replying nodes within the next search range is 1, and the wake-up signal corresponding to this threshold is transmitted. With these operations, the estimated value of $\theta$ and distribution of $\hat{G}$ are updated over time with the increase of collected data.

## IV. Numerical Results and Discussions

### A. Simulation Model and Parameters

The parameters employed in computer simulations are shown in Table I. In this study, the total number of sensor nodes, $N$, is assumed to be 50. The frame length employed for signaling the change of wake–up mode to UCWu mode is 10.96 [ms], and those for CU-CoWu and CD-CoWu are 11.12 [ms] and 11.28 [ms], respectively. The distribution is assumed to be a truncated Gaussian with the mean of 25 and the standard deviation of 2, that is, the true value to be estimated, $\theta$, is 25. It is assumed that the observed data of each node does not change during a data collection period. As a performance metric, we use the estimation error and the energy consumption required to achieve a certain required accuracy. The estimation error is the squared error of the parameter to be estimated. The simulation is conducted 1000 times, and the averaged results over simulation trials are shown below. In this work, we compare performance of ES method with that of UCWu, where data is collected solely with ID–based wake-up. With UCWu, data is collected in the increasing order of IDs. In this evaluation, we neglect the energy consumption of wake–up receiver since its value is same for the proposed ES method and UCWu. Only energy consumed by the main radio during active period of each node is considered for the comparison.

[1]Due to lack of space, we omit a mechanism to estimate the variance of $\hat{G}$ here, but we confirmed that its estimation can be accurately made with the proposed method.

TABLE I
SIMULATION PARAMETERS.

| | |
|---|---|
| Bit Rate | 100 kbps |
| Access control | CSMA/CA |
| $[V_{min}, V_{max}]$ | [0,50] |
| Data quantization interval $V_{step}$ | 0.1 |
| Length Step of Wake-up Frame [4] | 0.16msec |
| Minimum wake-up frame length $T_{min}$ [4] | 10.8msec |
| Wake-up Frame for UCWu signaling | 10.96msec |
| Wake-up Frame for CoWu signaling | 11.12msec (CU-CoWu)<br>11.28msec (CD-CoWu) |
| Wake-up Frame of UCWu | 11.28ms+0.16*$i$ [msec]<br>($i$: ID number) |
| Wake-up Frame of CoWu | 11.28ms+0.16*$j$ [msec]<br>($j$: quantization interval) |
| Max. Num. of Back-offs | 4 |
| macMinBE | 3 |
| macMaxBE | 5 |
| Max. Num. of Retransmissions | 3 |
| Power Consumption in TX state | 55 mW |
| Power Consumption in RX state | 50 mW |

### B. Simulation Results

Fig. 4 shows the estimation error of true value for UCWu and ES method against the number of sensor nodes whose data are collected. From this figure, we can see that the estimation error decreases as the number of nodes with their data collected increases for both methods. We can clearly see

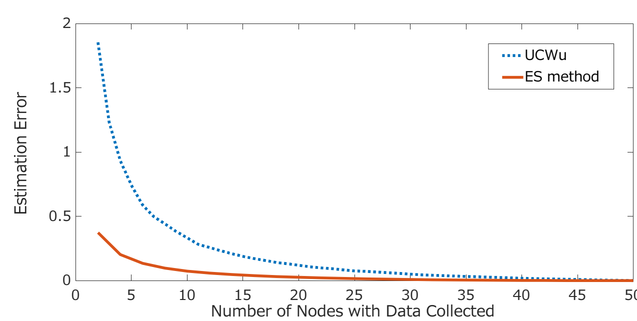


Fig. 4. Estimation error of true value against the number of nodes with their data collected for UCWu and ES method.

that the estimation with ES method has smaller error than UCWu for the same number of nodes with collected data. This is because the proposed ES method estimates the true value with an equal number of data of sensor nodes observing higher and lower side of distribution, which can reduce the error thanks to the line-symmetry of the truncated Gaussian distribution with respect to the mean. On the other hand, in UCWu, data is collected regardless of the observed value of the sensor nodes, and the estimated value tends to be biased to higher or lower value from the true value. This is the reason why UCWu exhibits larger error.

Next, we compare the energy consumption required to achieve a given estimation accuracy for UCWu and ES method. Here, the energy consumption is defined as the amount of energy consumed by sensor nodes for the duration of data collections, i.e., from the start of data collections to a timing where the sink collects data from the number of nodes required to achieve a given estimation error, which is here set to be 0.2 as an example. From Fig. 4, we can obtain the number of sensor nodes with their data collected to achieve an estimation error of 0.2: 16 sensor nodes in UCWu and 4 sensor nodes in ES method. In each method, when collecting data from the required number of nodes described above, 5.3 [mJ] is required for UCWu, and 2.8 [mJ] for ES method. In other wards, ES method can reduce the energy consumption to achieve the same estimation error by about 50 [%] in comparison to UCWu. This result confirms that ES method is superior to UCWu in terms of the energy consumption when achieving the required estimation accuracy.

### C. Comparison between the fixed and dynamic step size of ES method

As described in Sec. III, the proposed ES method can dynamically set the step size to search sensing data over the distribution with unknown mean and variance. In order to understand the benefit of this dynamic step size, here, we compare performance of ES method with dynamic and fixed step size. We show the energy consumption and delay required to collect sufficient number of data to achieve an estimation error of 0.2 with ES method employing dynamic step size and those with fixed $V_{step}$ of 0.5 and 0.8 in Table II. From this table, we can see that the proposed ES method with dynamic step size can well-control the trade-off between delay and energy consumption. For example, in order to achieve the same delay as dynamic step size, the fixed $V_{step}$ of 0.8 needs to be employed, however, in this case, the energy consumption of fixed $V_{step}$ is higher than that of the dynamic step size. On the other hand, in order to achieve the same level of energy consumption as dynamic step size, the fixed $V_{step}$ of 0.5 should be used, however, this results in larger delay than the dynamic step size. From this result, we can confirm that the proposed method can appropriately specify the data range to be searched dynamically, which enables us to simultaneously achieve small delay and low energy consumption for distributed estimation.

TABLE II
ENERGY CONSUMPTION AND DELAY OF ES METHOD WITH DYNAMIC AND FIXED STEP SIZE.

| Method | Delay [s] | Energy consumption [mJ] |
|---|---|---|
| Dynamic | 2.6 | 2.8 |
| $V_{step}$ = 0.5 (fixed) | 4.1 | 2.7 |
| $V_{step}$ = 0.8 (fixed) | 2.6 | 4.0 |

## V. CONCLUSIONS

In this paper, we focused on distributed estimation of an observation at a sensing target based on noisy sensing data collected from sensor nodes operating with wake-up receivers. Assuming a truncated Gaussian distribution of the sensed data, we proposed estimative sampling (ES) method, which can selectively wake up sensor nodes whose data can contribute to the improvement of estimation accuracy by exploiting the advantage of content-based wake-up (CoWu). We compared performance of ES method with that of UCWu that is an identity-based wake-up without considering the importance of each sensing data. Our numerical results obtained by computer simulations show that the proposed ES method is superior to UCWu in terms of energy consumption required to achieve the same estimation accuracy. We also confirmed that the dynamic step size employed in ES method can well-control the trade-off between delay and energy consumption.

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