Multiple Access System Designs via Genetic Algorithm in Wireless Sensor Networks

Shusuke Narieda
Akashi National College of Technology
Japan

1. Introduction

Recently, a distributed estimation, a type of parameter estimation problem, has been widely studied from the viewpoint of wireless sensor network (WSN) applications (1) (2). In particular, distributed estimation has been well-studied for certain WSN applications, such as environmental monitoring and precision agriculture (3)-(8). In such applications, measurements are acquired by the combination of a large number of deployed sensors which are equipped with a radio communication transceiver and a fusion center (FC), which collects measurement information from sensors to obtain a final estimate. Such measurement systems require some multiple access systems such as time division multiple access (TDMA), frequency division multiple access (FDMA) (9), frequency and time division multiple access (FTDMA) (10). However, most of related works ignore the effect of multiple access techniques on distributed estimation in WSNs.

This chapter describes a distributed estimation technique that uses genetic algorithm (GA) (11) to optimize the FTDMA which offers high reliability and spectral efficiency and is employed in several WSN systems (12) (13) and RFID systems as a multiple access technique (14). Mobile fusion center based WSN systems that enables ubiquitous physical data collection anywhere have been presented (15). However, because the devices involved in such systems do not typically employ an expensive or considerable hardware, their communication requirements are strictly limited. For instance, a high performance digital signal processor is required to cancel in-band channel interference at baseband in a low-IF receiver (16)-(23). First, the optimization problem based on a mean-squared error (MSE) function to obtain the final estimate is defined. Next, the effects of FTDMA-based measurement environment with WSN on the energy constrained distributed estimation are described, and we show that time slots and frequency bands should be allocated appropriately to avoid the effect of a large power interference (24). We define this problem as a combination optimization, and employ GA to solve this problem. Also, from these, we develop an algorithm to obtain the suboptimal time slot, frequency band and transmit power allocation for each sensor.

2. Preliminary notion

2.1 Frequency and time division multiple access

Fig.1 shows FTDMA models as the multiple access tecnique. In this model, the time is divided into N_T time slots with the same length and the available frequency is divided into N_F
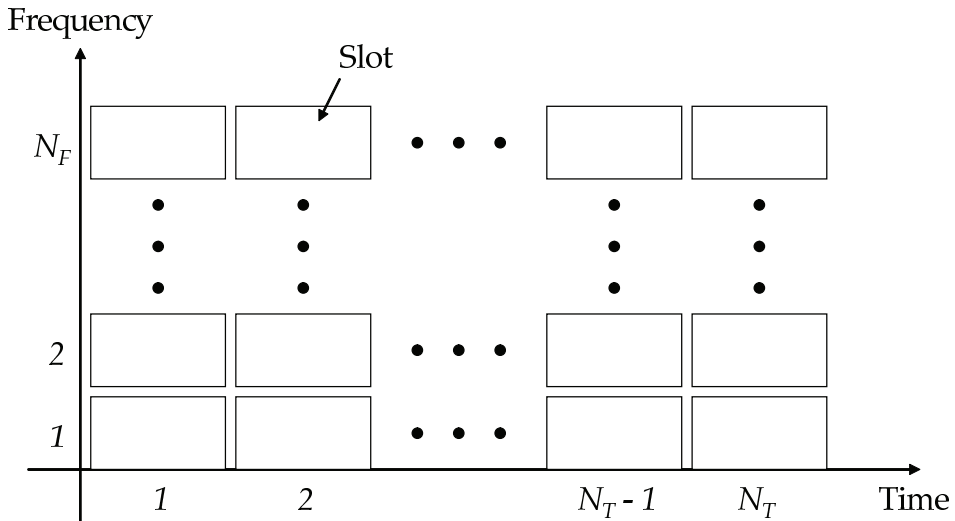
Frequency

Slot

Fig. 1. FTDMA system

frequency bands with the same bandwidth. Also, N_F time slots are transmitted at the same time for all available frequencies. Time slots are allocated to sensors to transmit observed quantities to the FC.

2.2 Multisensor measurement system with best linear unbiased estimator

In this subsection, we describe the distributed estimation model in FTDMA-based WSNs as shown in Fig.2. In this model, N spatially deployed senosrs observe unknown phenomena θ with zero mean and variance σ_θ^2. A local measurement at the ith node is corrupted by an additive noise as

$$x_i = \theta + n_i, \quad 1 \leq i \leq N \tag{1}$$

where n_i is spatially independent zero-mean additive measurement noise with variance $\sigma_{n_i}^2$. We assume that all $\sigma_{n_i}^2$ are known at the FC. Due to the bandwidth limitation, each sensor quantizes x_i with a quantization function $\mathcal{Q}(\cdot)$ into b-bit messages as

$$m_i = \mathcal{Q}(x_i), \quad 1 \leq i \leq N. \tag{2}$$

In this chapter, we adopt an uniform quantization scheme as $\mathcal{Q}(\cdot)$. The quantization message m_i can be written with a quantization error as

$$m_i = x_i + q_i, \quad 1 \leq i \leq N \tag{3}$$

where q_i is the quantization error uniformly distributed with zero mean and variance $\sigma_{q_i}^2 = W^2/(3 \cdot 2^{2b_i})$, where $[-W, W]$ is the available signal amplitude range and b_i is the allocated
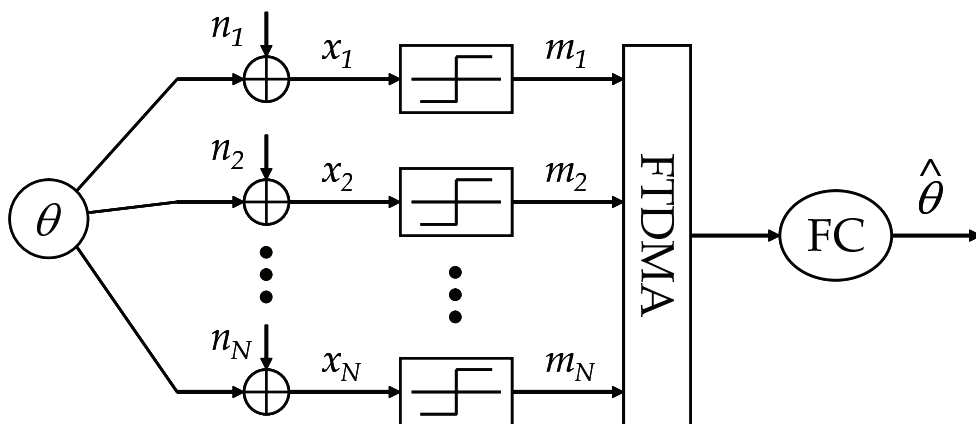
Fig. 2. System model

bit to ith sensor. The FC is gathered quantization message m_i and combined to generate final estimate of $\hat{\theta}$. $\hat{\theta}$ can be obtained by the best linear unbiased estimator (BLUE) (25) as

$$\hat{\theta} = \left(\sum_{i=1}^{N} \frac{1}{\sigma_{n_i}^2 + \sigma_{q_i}^2} \right)^{-1} \left(\sum_{i=1}^{N} \frac{m_i}{\sigma_{n_i}^2 + \sigma_{q_i}^2} \right). \tag{4}$$

The MSE D is given as

$$D = \left(\sum_{i=1}^{N} \frac{1}{\sigma_{n_i}^2 + \sigma_{q_i}^2} \right)^{-1}. \tag{5}$$

3. Communication systems

3.1 Modulation scheme

In this subsection, we describe communication systems in the distributed estimation model. In this chapter, we consider multilevel quadrature amplitude modulation (QAM) which is a popular digital modulation schemes. To characterize QAM modulated signals, we employ the transmission energy model (26) as

$$\bar{P}_i(b_i) = c_i \cdot d_i^{\alpha} \left(\ln \frac{2}{p_i} \right) \cdot (2^{b_i} - 1), \quad \forall i \tag{6}$$

where c_i, d_i, α and p_i is a system constant related with an analog circuit, a transmission distance between ith sensor and the FC, the pathloss exponent, and a probability of bit error, respectively. In this chapter, we assume that the electrical and communication requirement for all sensor nodes are the same, i.e., $c_i = c$ and $p_i = p$, and we define a normalized transmission

energy model as

$$P_i(b_i) = d_i^\alpha \cdot (2^{b_i} - 1), \quad \forall i. \tag{7}$$

Here, we consider the effect of a decision error of a bit in quantized messages m_i on D. It can be seen that error free communication systems are considered in previous subsection. However, modulated signals are distorted from the additive white Gaussian noise, and received messages $\hat{m}_i$ may be not equal to m_i. As a result, an obtained MSE $\hat{D}$ may be larger than D. From these, it can be considered that D represents a lower bounds of the obtained MSE. Although D can be interpreted as mentioned above, we assume that D is the MSE which is defined in eq.(5) to simplify description and explanation.

3.2 Adjacent and in-band channel interferences

Heterodyne receivers may be most widely used architecture in narrowband communication systems. In the architecture, a low intermediate frequency (IF) receiver can be implemented with high degree of integration, and it is suited to the wireless communication terminal which is required the transceiver miniaturization. The low-IF architecture is equipped an analog-to-digital converter (ADC) at the processing stage of an IF signal, and the fact provides a good performance for an in-band and adjacent channel interference cancellation because of digital signal processing techniques, e.x., filtering (16)-(23). However, a digital filter for such processing is required a steep characteristic, and it causes the computational complexity.

In this subsection, we describe the narrowband wireless communication systems with $\bar{N}$ communication channels. The receiver model discussed in this chapter is shown in Figs.3 and 4. In the architecture, a radio frequency (RF) signal is received by an antenna and passed through a band pass filter (BPF) such as a surface acoustic wave (SAW) filter and a low noise amplifier (LNA). The receiver has Hartley image canceller in analog circuits to cancel image band interferences. Under the assumption that there are no an I/Q imbalance (16) in these analog circuits, IF signals, which is the desired signal and in-band channel interference including the adjacent channel interference, are sampled and quantized at the ADC. A filtered and an amplified RF signal $r_{\mathrm{RF}}(t)$ is down converted into the IF signal $r_{\mathrm{IF}}(t)$ at a quadrature mixer with the frequency f_{LO}, where f_{LO} is the local oscillator frequency and $f_{\mathrm{LO}} = f_{\mathrm{RF}} - f_{\mathrm{IF}}$, f_{RF} and f_{IF} are the RF and IF frequency, respectively. $r_{\mathrm{IF}}(t)$ can be written by

$$r_{\mathrm{IF}}(t) = d_{\mathrm{IF},i}(t) + \sum_{j=0, j\neq i}^{N_{\mathrm{IF}}-2} z_{\mathrm{IF},j}(t) + v_{\mathrm{IF}}(t), \qquad 0 \leq i \leq N_{\mathrm{IF}} - 1 \tag{8}$$

where $d_{\mathrm{IF},i}(t)$, $z_{\mathrm{IF},j}(t)$, $v_{\mathrm{IF}}(t)$, and N_{IF} is the desired IF signal at ith communication channel, the in-band channel interferences IF signal at jth communication channel, the additive gaussian noise and the number of communication channels at IF band, respectively. The value of N_{IF} depends on the bandwidth of the IF filter and the channel index i, therefore, $\bar{N} \leq N_{\mathrm{IF}}$. Also, illustrations of $r_{\mathrm{IF}}(t)$ on a frequency domain are shown in Fig.5. Then, the desired signal has a center frequency f_{IF}. After passing through the ADC, $r_{\mathrm{IF}}(n)$ is down-converted into the baseband signal $r_{\mathrm{B}}(n)$ at a digital quadrature mixer with the frequency f_{IF} as shown in Fig.4. Since the center frequency of the desired signal is f_{IF}, $r_{\mathrm{B}}(n)$ can be written in the following
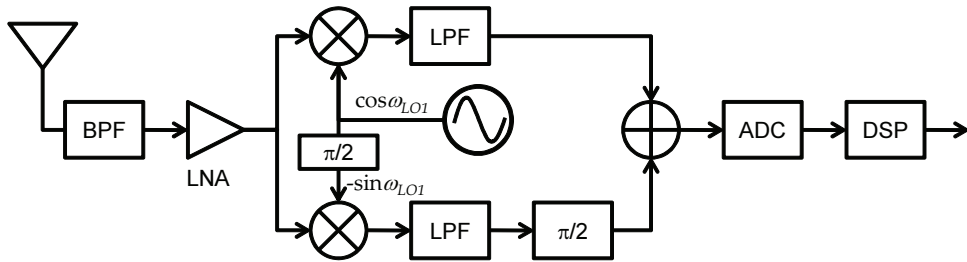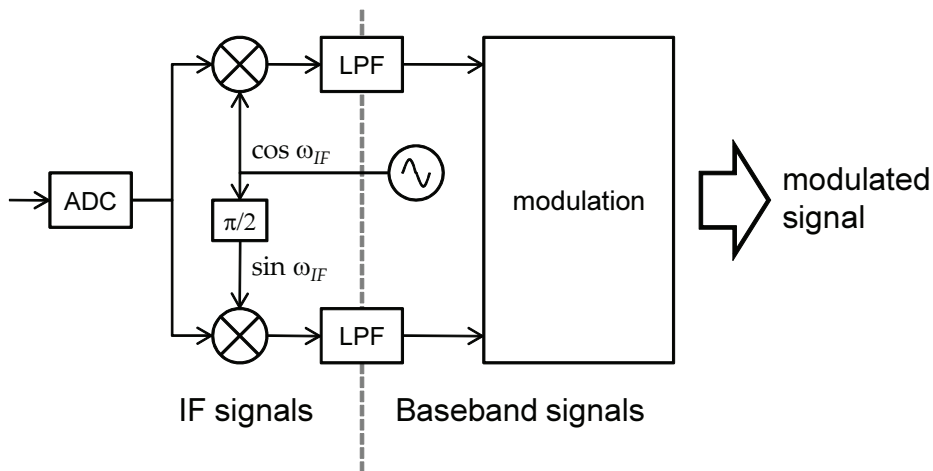
Fig. 3. Low-IF architecture

Fig. 4. General digital signal processing part in low-IF receiver

equation,

$$r_{\text{B}}(n) = d_{\text{B}}(n) + \sum_{j=1}^{N_{\text{B}}-1} z_{\text{B},j}(n) + v_{\text{B}}(n) \tag{9}$$

where $v_{\text{B}}(n)$ is the additive gaussian noise, and $v_{\text{B}}(n) \sim \mathcal{N}(0, \sigma_v^2)$, $d_{\text{B}}(n)$ and $z_{\text{B},i}(n)$ are desired signal and interference at ith communication channel respectively. N_{B} is the number of communication channels at baseband and $N_{\text{IF}} \geq N_{\text{B}}$. Also, $z_{\text{B},1}(n)$ is called as the adjacent channel interference. Fig.6 shows baseband signals including the desired signal, adjacent and in-band channel interference in a frequency region. Note that the desired baseband signal is moved to the frequency range around the DC. Let $f_{\text{B,max}}$ denotes the maximum frequency of all baseband signal component including desired signal, adjacent and in-band channel interferences. Although the minimum sampling frequency of the baseband signal $f_{S,\text{min}}$ equals to $2f_{\text{B,max}}$, the sampling frequency of the low-IF receiver is more higher than $f_{s,\text{min}}$ because IF signal with higher frequency than the baseband signal are sampled in the low-IF receiver.
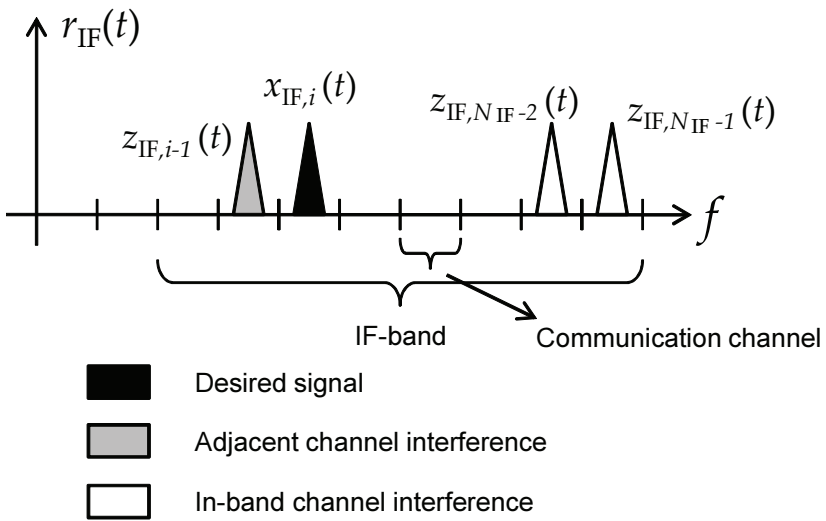
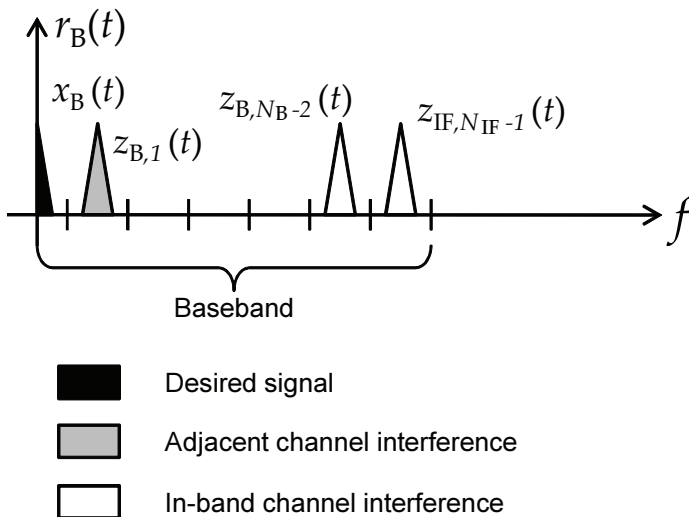Fig. 5. IF signals in low-IF receiver

Fig. 6. Baseband signals in low-IF receiver

4. Distributed estimation techniques in FTDMA-based WSN

In this section, we discuss the distributed estimation technique in FTDMA-based WSN. At first, we define an optimization problem to obtain a solution for the distributed estimation.

Next, we derive the equation of the power allocation based on the defined optimization problem. Also, we show that the solution of the problem can not be obtained without optimization of a combination of sensors in tth time slot, and develop the algorithm to obtain suboptimal solution.

4.1 Problem setup

At first, we define an all sensor set $\bar{S}_0$ as

$$i \in \bar{S}_0, \quad 1 \leq i \leq N. \tag{10}$$

Also, the set $\bar{S}_0$ can be partitioned into N_T sensor subsets S_t as

$$\bar{S}_0 = \bigcup_{1 \leq t \leq N_T} S_t. \tag{11}$$

The S_t means the subset of sensors which transmit message in tth time slot.

Next, we define the problem while keeping a total power constraint which is the sum of transmit powers of individual sensor at the same time. As shown in previous section, received signals in narrowband communication systems are corrupted by the adjacent and in-band channel interferences. Interferences having a large power cannot be canceled without the LPF which has steep characteristics, ans such the LPF is incurred the large number of multiplyer and register because the length of the impluse response of the LPF is very long. Therefore, maximum total power of these interferences at the same time slots is strictly limited. From these, we define the optimization problem as (24)

$$\begin{aligned} \underset{b_i \in \mathbb{Z}^+}{\arg\min} \quad & \left(\sum_{i=1}^{N} \frac{1}{\sigma_{n_i}^2 + \sigma_{q_i}^2} \right)^{-1} \\ \text{subject to} \quad & \mathcal{P}_{tot} \geq \sum_{i \in S_t} a_i \cdot (2^{b_i} - 1) \\ & \sigma_{q_i}^2 = W^2 / (3 \cdot 2^{2b_i}) \end{aligned} \tag{12}$$

where $a_i = d_i^\alpha$, $\mathbb{Z}^+$ denotes the set of all nonnegative integers, and $\mathcal{P}_{tot}$ is the normalized total power constraint at the same time slots.

However, the solution of eq.(12) can not be obtained via a convex optimization. In this chapter, to facilitate analysis of eq.(12), since $b_i \in \mathbb{Z}^+$, it follows $\sum_{i \in S_t} a_i(2^{b_i} - 1) \leq \sum_{i \in S_t} a_i(2^{b_i} - 1)(2^{b_i} + 1)$ and $(2^{b_{\min}} + 1) \leq (2^{b_i} + 1)$ where $b_{\min}$ represents the number of the smallest allocatable bits. From these, we introduce the constraint defined as follows (24),

$$(2^{b_{\min}} + 1)\mathcal{P}_{tot} \geq \sum_{i \in S_t} a_i(2^{2b_i} - 1). \tag{13}$$

Eq.(13) is the equation based on the constraint in eq.(12), and we can replace the power constraint in eq.(12) by eq.(13) without violating the total power requirement. A similar replacement technique, which represents $\mathcal{P}_{tot} \geq \sum_{i \in S_t} a_i(2^{b_i} - 1)$, has been reported (4). As shown in the comparison of two equations, our technique can use the available transmit

power effectively. In fact, b_{min} is equal to zero, in which the case corresponds that there is no allocatable bit to ith sensor.

From these, by performing a change of variable with $\beta_i = 2^{2b_i}$ and some modification, the optimization problem is redefined as

$$
\begin{aligned}
&\underset{\beta_i \in \mathbb{R}^+}{\arg\max} \sum_{i=1}^{N} \frac{Q\beta_i}{\sigma_{n_i}^2 Q\beta_i + 1} \\
&\text{subject to } 2 \cdot \mathcal{P}_{tot} \geq \sum_{i \in \mathsf{S}_t} a_i \cdot (\beta_i - 1) \\
&\qquad\qquad \beta_i \geq 0
\end{aligned}
\tag{14}
$$

where $\mathbb{R}^+$ denotes the set of all nonnegative real number and $Q = 3/W^2$. β_i is relaxed to a nonnegative real number so as to render the problem tractable. In eq.(14), once the optimal β_i is obtained, b_i is determined through upper integer rounding, as (3)-(5).

4.2 Power allocation and sensor selection in FTDMA-based WSN

In eq.(14), when $N_T = 1$, which is similar to conventional method as (3)-(5), the solution of the optimization problem can be obtained by Lagrangian multiplier (27) associated with the equality the total power constraint and inequality constraint. In the case of $1 < N_T < N$, which requires using several frequency bands, the solution of eq.(14) can not be obtained with the solving method for $N_T = 1$. In this subsection, we discuss how to obtain the solution of eq.(14), when $1 < N_T < N$. In this case, the solution of eq.(14) can be obtained by following Lagrangian J

$$
J = -\sum_{i=1}^{N} \frac{Q\beta_i}{\sigma_{n_i}^2 Q\beta_i + 1} - \sum_{t=1}^{N_T} \lambda_t \left\{ 2 \cdot \mathcal{P}_{tot} - \sum_{i \in \mathsf{S}_t} a_i \cdot (\beta_i - 1) \right\} - \sum_{i=1}^{N} \nu_i \beta_i
\tag{15}
$$

where λ_t and ν_i is equality and inequality constraints as Lagrange multiplier, respectively. Eq.(15) leads to the following Karush-Kuhn-Tucker (KKT) conditions (25)

$$
\begin{aligned}
&-\frac{Q}{\left(\sigma_{n_i}^2 Q\beta_i + 1\right)^2} + \lambda_t a_i - \nu_i = 0, \ \forall t, i \in \mathsf{S}_t \\
&2 \cdot \mathcal{P}_{tot} - \sum_{i \in \mathsf{S}_t} a_i \cdot (\beta_i - 1) = 0, \ \forall t \\
&\qquad\qquad \nu_i \beta_i = 0, \ \forall i \\
&\qquad\qquad \nu_i \geq 0, \ \forall i \\
&\qquad\qquad \beta_i \geq 0, \ \forall i.
\end{aligned}
\tag{16}
$$

From the first equation in eq.(16), β_i can be obtained as

$$
\beta_i = \frac{Q}{\sigma_{n_i}^2} \left(\frac{1}{\sqrt{Q\lambda_t a_i - \nu_i}} - 1 \right), \quad \forall t, i \in \mathsf{S}_t.
\tag{17}
$$

Also, we can see from the third equation that for those sensors with $\beta_i \geq 0$, ν_i holds. Therefore

$$\beta_i = \frac{Q}{\sigma_{\tilde{n}_i}^2} \left(\frac{1}{\sqrt{Q\lambda_t a_i}} - 1 \right)^+, \quad \forall t, i \in S_t \tag{18}$$

where $(\mathcal{X})^+$ equals to 0 when $\mathcal{X} < 0$, and is otherwise equals to $\mathcal{X}$. The Lagrange multiplier λ_t can be obtained by substituting β_i into the second equation in eq.(16) as

$$\lambda_t = \left(\frac{Q \sum\limits_{i \in S_t}^{N_F^{(t)}} \frac{\sqrt{a_i}}{\sigma_{\tilde{n}_i}^2}}{2 \cdot \mathcal{P}_{tot} + \sum\limits_{i \in S_t}^{N_F^{(t)}} a_i \left\{ \frac{Q}{\sigma_{\tilde{n}_i}^2} + 1 \right\}} \right)^2, \quad \forall t. \tag{19}$$

where $N_F^{(t)}$ is the number of active sensors in tth time slot, and $1 \leq N_F^{(t)} \leq N_F$. $N_F^{(t)}$ is determined such that $f\left(N_F^{(t)}\right) \geq 1$ and $f\left(N_F^{(t)} - 1\right) < 1$, where $f(\cdot)$ is the function which is defined as

$$f\left(N_F^{(t)}\right) = \frac{1}{\sqrt{Q\lambda_t \left(N_F^{(t)}\right) a_i}} \tag{20}$$

where $\lambda_t(\cdot)$ is the rewritten version of λ_t and represents the function of the number of active sensor. We assume that sensors are ranked according to a_i such as $a_1 \geq \cdots \geq a_{N_F^{(t)}}$, and the optimal bit load b_i^{opt} can be obtained as

$$b_i^{opt} = \begin{cases} \frac{1}{2} \log_2 \left\{ \frac{Q}{\sigma_{\tilde{n}_i}^2} \left(f(N) - 1 \right) \right\} & \text{for } 1 \leq N \leq N_F^{(t)} \\ 0 & \text{for } N_F^{(t)} < N \leq N_F \end{cases} \tag{21}$$

4.3 Selection for combination of sensors in subset S_t

The solving method derived in previous subsection is not yet enough to solve the power (or information bit) allocation problem in FTDMA-based WSN, since the subset S_t which represents the combination of sensors transmit at tth time slot is not determined. From the solving method, it can be seen that β_i is determined from the distance parameter a_i and measurement noise variance of sensors in S_t. Obtained β_i may be different when combinations of sensors in S_t are different. Moreover, the MSE D is a nonlinear function for β_i as shown in the following equation which is rewritten version of eq.(5) with β_i,

$$D = \left(\sum_{i=1}^{N} \frac{1}{\sigma_{\tilde{n}_i}^2 + W^2 / (3 \cdot \beta_i)} \right)^{-1}. \tag{22}$$

Hence, it can be considered that obtaining the MSE depends on combinations of sensors in each S_t, and when $1 < N_T < N$, the combination of sensors in subset S_t must be determined appropriately, i.e., S_t optimization. Here, we rewrite the MSE function representation D to $D(\bar{\mathsf{S}}_0)$ as a function of sensors set $\bar{\mathsf{S}}_0$, and this problem can be written as a combination optimization problem as

$$[\hat{\mathsf{S}}_1, \cdots, \hat{\mathsf{S}}_{N_T}] = \arg\max_{\mathsf{S}_1, \cdots, \mathsf{S}_{N_T}} \left\{ D\left(\bar{\mathsf{S}}_0\right)^{-1} \right\} \tag{23}$$

$$2 \cdot \mathcal{P}_{tot} \geq \sum_{i \in \mathsf{S}_t} a_i \cdot (\beta_i - 1) \tag{24}$$

$$\beta_i \geq 0, \quad 1 \leq t \leq N_T \tag{25}$$

where $\hat{\mathsf{S}}_t$ is a suboptimal sensors subset. To solve this problem, we employ GA which is utilized to efficiently solve the combination optimization.

From these, we develop an algorithm to obtain a suboptimal combination of sensors in subset $\hat{\mathsf{S}}_t$. The flowchart of the developed algorithm is shown in Fig.7. In Fig.7, at first, M individuals are initialized, where M is population size. The mth individual can be represented by $1 \times N$ vector $\mathbf{k}_{(j,m)}$ as

$$\mathbf{k}_{(j,m)} = \left[\kappa_1^{(j,m)}, \cdots, \kappa_N^{(j,m)} \right], \quad 1 \leq m \leq M \tag{26}$$

where the gene $\kappa_i^{(j,m)}$ represents the time slot index to be ith sensor transmitted and the value of $\kappa_i^{(j,m)}$ can take the integer value as $\kappa_i^{(j,m)} = 0, 1, \cdots, N_T$, and when the number of available time slot is smaller than the number of sensor, $\kappa_i^{(j,m)}$ may be equal to 0. Also, the total number of $\kappa_i^{(j,m)}$ with same value is limited by the available frequency band N_F. Several GA operations, i.e., selection, crossover and so on, are carried out to $\mathbf{k}_{(j,m)}$.

In our developed algorithm, a subset $\hat{\mathsf{S}}_t^{(j,m)}$ which represents the subset of sensors obtained from mth individuals at jth generation can be obtained at every generation. $\hat{\mathsf{S}}_t^{(j,m)}$ is determined by $\mathbf{k}_{(j,m)}$ as

$$\hat{\mathsf{S}}_t^{(j,m)} \ni \left\{ i \,\middle|\, \kappa_i^{(j,m)} = t \right\}, \quad \forall i. \tag{27}$$

$\hat{\mathsf{S}}_t^{(j,m)}$ determines the MSE $D_{(j,m)}\left(\bar{\mathsf{S}}_0\right)$ to rank mth individuals at jth generation. Also, the number of $\kappa_i^{(j,m)}$ with the same value is counted after the initialization and GA operation for $\mathbf{k}_{(j,m)}$. If the total number of $\kappa_i^{(j,m)}$ with same value exceeds N_F, it is allocated to other time slot other than N_F sensors.

After finishing the developed algorithm, the $\mathbf{k}_{(j,k)}$ provides a suboptimal combination of sensors in subset $\hat{\mathsf{S}}_t$, $\forall t$, namely, the time slot and frequency band allocation for all sensors. The allocated power for all sensors can be obtained from eq.(18).
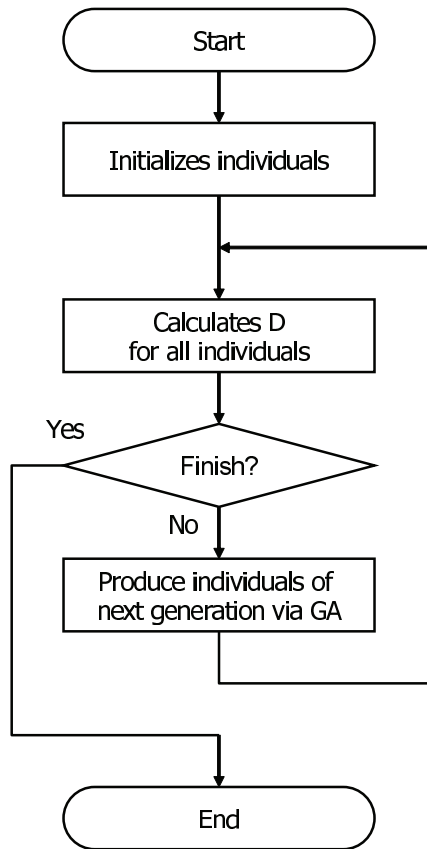
Fig. 7. Flowchart of the algorithm combined power allocation and combination optimization to solve the optimization problem.

5. Numerical examples

In this section, to evaluate the performance of the algorithm shown in Fig.7, numerical simulations are carried out. At first, we show GA operations and parameter employed in this chapter. We employ an elite selection scheme and one point crossover, also, only one gene is mutated at a mutation step in GA. In our numerical simulations, for GA, the number of elite, population and mutation ratios are selected as 5, 50 and 1, respectively. Individual vectors $\mathbf{k}_{(j,m)}$ are initialized uniformly distributed for all time slots in the initialization step. Also, results shown in this section are obtained by averaging over 500 independent trials.

In order to evaluate the algorithm, we compare two curves which were obtained by i) the algorithm shown in previous section, and ii) averaged result in initialized individuals in population. In these, i) corresponds to the results obtained from algorithm with $\mathbb{R}_t$ optimization, and ii) corresponds to the result obtained from conventional sensor selection,

i.e., without $\mathbb{R}_t$ optimization. In the following results, σ_θ^2 equals 1, and pathloss coefficients $a_i = d_i^\alpha$ are generated by a uniformly distributed $d_i \in [1, 10]$, and we use $\alpha = 2$ which is the almost same value in literatures (3)-(8) assuming same environments to this chapter. In this chapter, to evaluate the heterogeneous sensor environment, we adopt the normalized deviation of random variables $\psi(\cdot)$ as

$$\psi(R) = \frac{\sqrt{\text{var}R}}{E[R]}. \tag{28}$$

Also, to describe statistical information of sensor noise variance, we adopt the commonly used following equation (3)-(8)

$$\sigma_{n_i}^2 = 0.1 + \gamma \chi_{1,i}^2, \quad 1 \le i \le N. \tag{29}$$

where $\chi_{1,i}^2$ is the Chi-square distribution of degree 1, γ controls the underlying variation from the nominal minimum.

Fig.8 shows the MSE performance versus measurement noise variance for several number of time slots when $N_F = 10$, $N = 300$ and $\mathcal{P}_{tot} = N$. For all curves in Fig.8, MSE
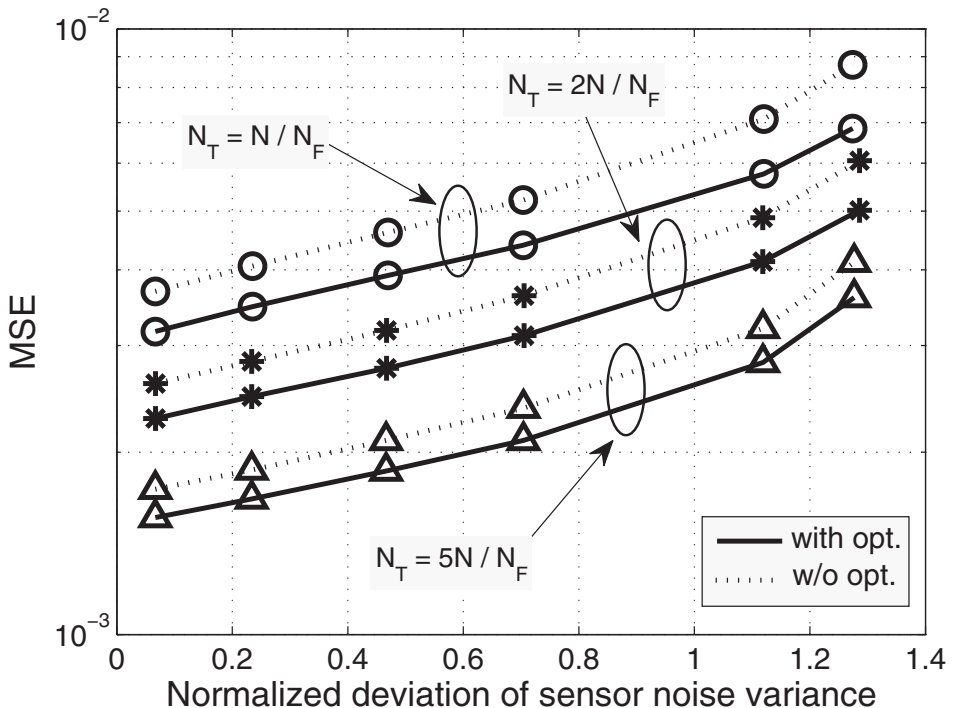

Fig. 8. MSE performance versus normalized deviation of sensor noise variance for the number of different time slot
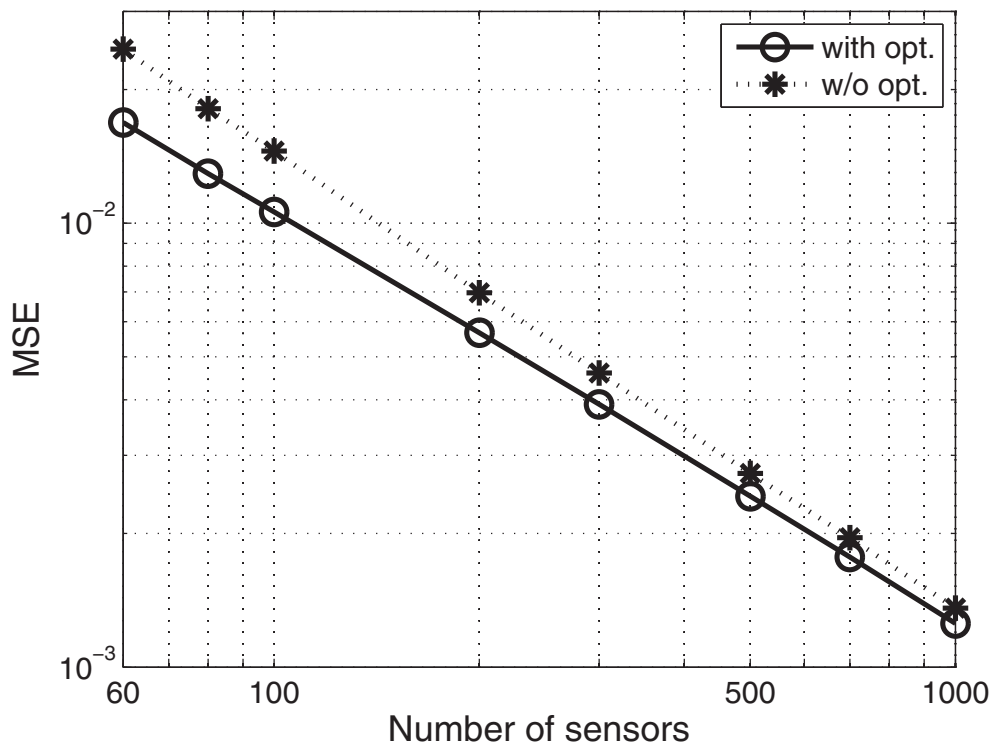
Fig. 9. MSE performance versus the number of sensors with $N_F = 10$, $N_T = N/N_F$, $\psi(n_i) = 0.47$ and $\mathcal{P}_{tot} = 300$.

performances are improved as the number of time slot increases, and it can be considered available transmit power per one active sensor increases as the number of N_T increases. The algorithm outperforms the algorithm without $\mathbb{R}_t$ optimization. Also, it can be seen that MSE performances are improved effectively as the number of N_T decreases, i.e., the density of sensors in FTDMA-based WSN increases.

Fig.9 shows that MSE performances versus the number of sensors when $N_F = 10$, $N_T = N/N_T$, $\mathcal{P}_{tot} = 300$ and $\phi(n_i) = 0.47$, and these conditions represent the number of available frequency band is fixed. From Fig.9, it can be seen that MSE performances are improved as N increases for two curves and our algorithm outperforms the algorithm without $\mathbb{R}_t$ optimization for all plots. In the contrast, the results for the fixed N_T case are shown in Fig.10. In Fig.10, MSE performances versus the number of sensors when $N_T = 10$, $N_F = N/N_T$, $\mathcal{P}_{tot} = 30 \cdot N_F$ and $\psi(n_i) = 0.47$, respectively. It can be seen that the fixed N_F case and the fixed N_T case have similar characteristics. Therefore, for an arbitrary N, $N_F < N_T$ is desirable to achieve measurement systems in FTDMA-based WSN with high spectral efficiency.
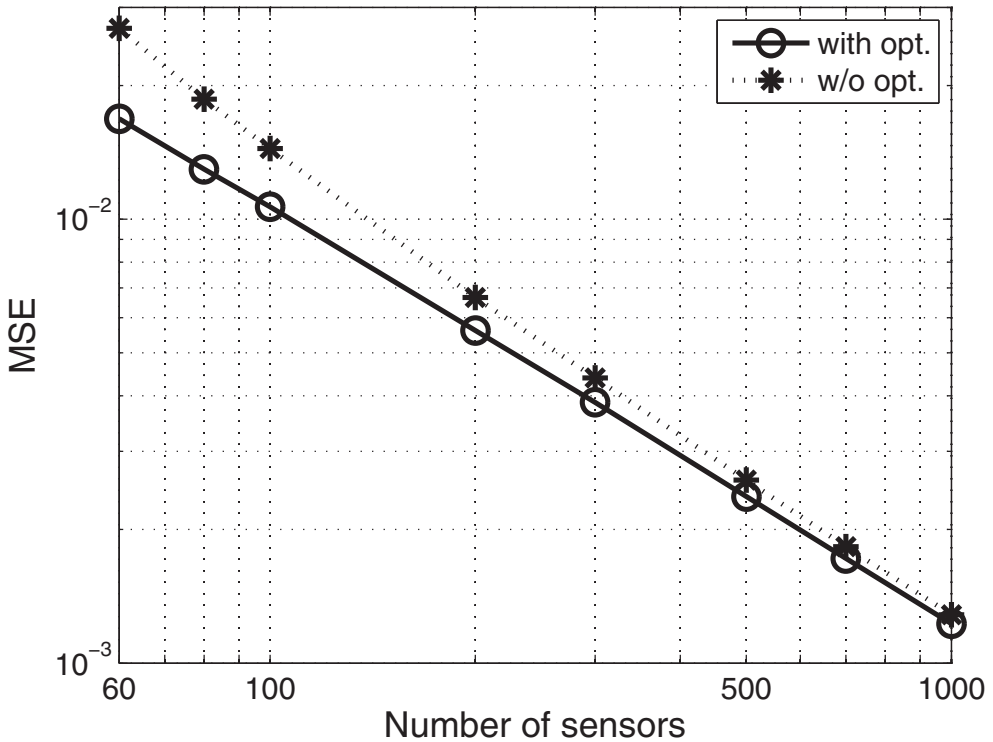
Fig. 10. MSE performance versus the number of sensors with $N_F = N/N_F$, $N_T = 10$, $\psi(n_i) = 0.47$ and $\mathcal{P}_{tot} = 30N_T$.
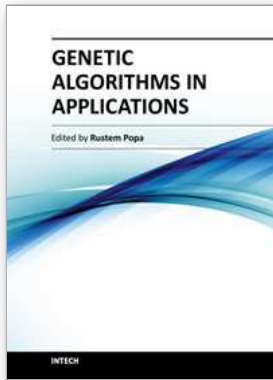
6. Conclusion

This chapter described the energy constrained distributed estimation in FTDMA-based WSN. The distributed estimation problem in FTDMA-based WSN has been formulated. Several equations for the bit allocation and the replacement technique of total power constraint in the problem have been derived. Also, the effect of FTDMA employed WSN on the distributed estimation has been investigated. We show that the time slot and frequency band to be allocated to each sensor must be optimized for the MSE minimization since the MMSE function is nonlinear for the number of allocated bit to each sensor. The problem of the combination of sensor determination in tth time slot has been defined as the combination optimization, we have employed GA to solve this problem. The algorithm to determine the time slot, frequency band, and the number of allocated bit to each sensor has been developed. Numerical examples have been presented. Our developed algorithm outperforms conventional sensor selection without optimization for the combination of sensors in terms of mean-squared error.

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Genetic Algorithms in Applications

Edited by Dr. Rustem Popa

Genetic Algorithms (GAs) are one of several techniques in the family of Evolutionary Algorithms - algorithms that search for solutions to optimization problems by "evolving" better and better solutions. Genetic Algorithms have been applied in science, engineering, business and social sciences. This book consists of 16 chapters organized into five sections. The first section deals with some applications in automatic control, the second section contains several applications in scheduling of resources, and the third section introduces some applications in electrical and electronics engineering. The next section illustrates some examples of character recognition and multi-criteria classification, and the last one deals with trading systems. These evolutionary techniques may be useful to engineers and scientists in various fields of specialization, who need some optimization techniques in their work and who may be using Genetic Algorithms in their applications for the first time. These applications may be useful to many other people who are getting familiar with the subject of Genetic Algorithms.

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