Low-Power Beam-Switching Technique for Power-Efficient Collaborative IoT Edge Devices

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Abstract: Collaborative beamforming (CB) enables uplink transmission in a wireless sensor network (WSN) composed of sensors (nodes) and far-away access points (APs). It can also be applied to the case where the sensors are equipped with beam-switching structures (BSSs). However, as the antenna arrays of the BSSs are randomly headed due to the irregular mounting surface, some sensors form beams that do not illuminate a desired AP and waste their limited energy. Therefore, to resolve this problem, it is required to switch the beams toward the desired AP. While an exhaustive search can provide the globally optimal combination, a greedy search (GS) is utilized to solve this optimization problem efficiently. Simulation and experimental results verify that under certain conditions the proposed algorithm can drive the sensors to switch their beams properly and increase the received signal-to-noise ratio (SNR) significantly with low computational complexity and energy consumption.

Keywords: IoT; low-power; collaborative beamforming; beam switching; greedy search

1. Introduction

Wireless sensors have been extensively employed for monitoring applications due to their potential reliability and scalability over limited-access areas [1–17]. To enable wireless sensors in IoT [18] to sense the surrounding environment over a wide frequency spectrum, integrated sensing circuits composed of magnetic [19], thermal [20], visual [21], infrared [22], and acoustic [23] radars are embedded in them. However, for their data communication, single omnidirectional antennas have been conventionally investigated owing to their simple structures and ability to share the sensed information simultaneously with neighboring sensors [24], as depicted in Figure 1a.

Whereas, the omnidirectional radiation causes weak connectivity and strong interference between sensors [25,26]. Although these drawbacks can be alleviated by utilizing directional antennas which provide the additional performance enhancement in terms of energy, throughput, spectrum, and security [27–29], directional antennas may not be suitable for sensors due to their reduced angular coverage and unsteerable radiating directions, as seen in Figure 1b, [30]. Fortunately, with the advent of Radio-Frequency Micro-Electromechanical Systems (RF-MEMS) components (e.g., phase shifters and switches) and miniaturized antennas, the beam-switching structures (BSSs) in Figure 2a can be used as one of the alternatives [31–36]. This is because they can generate directional beams toward one of the predetermined discrete directions and consequently provide the enhanced angular coverage [37], as illustrated in Figure 2b. Thus, in this paper, the scenario in which each of the sensors is equipped with a simple BSS is focused.

When a certain sensor needs to send the collected data to one of the APs, direct uplink would be preferable due to its low latency. However, considering the negative characteristics of WSNs (e.g., battery-powered sensors and severe path loss caused by far-away APs) [38–40], it would be prohibited in common cases. To tackle this limitation,
Ochiai et al. proposed the concept of the CB to add the radio signal of sensors constructively in the desired direction, and they demonstrated its remarkable performance over uniformly distributed sensors [41]. Furthermore, Ahmed et al. and Huang et al. conducted research on Gaussian and arbitrary distribution, respectively [42,43]. From the discussions of the above and other authors, it has been verified that the CB can form a directional beam, as shown in Figure 3, and is prominently helpful to achieve power improvement [44] in the direction of a desired AP (theoretically, proportional to the square of the number of sensors) [45–57]. Their work also show that the CB can increase the success probability of long-range direct transmission regardless of distribution of sensors.

Figure 1. The scenario that sensors (colored dots) have (a) omnidirectional or (b) directional radiators.

Figure 2. (a) The configuration of a beam-switching structure (BSS). (b) The beampatterns of sensors (colored dots) having BSSs.
Although the CB was originally designed for distributed omnidirectional radiators [58], it can also be applied to our scenario due to its simplicity. For the CB, sensors should switch their beams toward the desired AP by exploiting the position information of sensors and an AP, extracted from a reference position system such as the Global Positioning System (GPS). However, due to the irregular surface on which sensors are mounted, it could not be guaranteed that all of the switched beams would illuminate the proper angular range. Accordingly, it is anticipated that a serious reduction of the received power at the AP, resulting from the absence of some sensors in the CB, will occur. To avoid this problem, there are two approaches: (1) each sensor performs the beam switching in turn, or (2) all of the sensors do it simultaneously in a random manner. However, considering the innate restrictions of wireless sensors such as low power capacity and time-variant channel condition, the first approach which switches the beams of the sensors simultaneously is utilized.

In this paper, the received signal-to-noise ratio (SNR) at the desired AP is investigated to confirm the above speculation first. The algorithm to resolve the beam-switching problem with the goal of improving the SNR above a certain level, which is based on the GS requiring low computing capability, is also designed. Finally, through simulations and experiments, it is verified that the proposed algorithm can increase the SNR considerably, and is applicable in an embedded system having a Micro Controller Unit (MCU), which is widely used for wireless sensors.

2. System Model and Motivation

The symbols, which we used in this proposed system models, are summarized in Table 1. As observed in Figure 4, uplink data transmission between a WSN having $N$ sensors, $N = \{n_1, \ldots, n_N\}$, and an AP, $AP$, being far from $N$, is considered. Both the terminals are positioned in the $x - y$ plane, and their polar coordinates are represented as $(r_n, \psi_n)$ and $(A, \phi_0)$, respectively. Each sensor is equipped with a BSS with an antenna array connected to a beam switching matrix and circuit, and this selects one of the directional beams for the transmission. It is also assumed that due to the power constraint of wireless
sensors and the limited number of antennas in BSSs, there are no direct uplinks between each sensor and AP. As shown in Figure 5, the beampattern of the BSS is simply defined as

\[
\hat{B}(\Theta_{i,n}) = \begin{cases} 
N_t & \text{if } \phi_n(\varphi) \in \Xi_{i,n} \\
0 & \text{if } \phi_n(\varphi) \notin \Xi_{i,n},
\end{cases}
\]

where \( \Theta_{i,n} = \frac{\pi(2i-N_t-1)}{N_t} \) is the steering angle of the \( i \)th beam with \( i \in \{1, \cdots, N_t\} \), \( \phi_n(\varphi) \) is the local azimuth angle of \( n \), \( \varphi \in [-\pi, \pi) \) is the global azimuth angle, and \( \Xi_{i,n} = \left[ -\frac{\pi}{N_t} + \Theta_{i,n}, \frac{\pi}{N_t} + \Theta_{i,n} \right] \) is the azimuth interval with \( \Xi_{i,n} \cap \Xi'_{i,n} = \emptyset \) for \( i \neq i' \).

**Figure 4.** The system model (a) without or (b) with the effect of irregular mounting surface.

**Figure 5.** The beampatterns of the BSS with \( N_t = 3 \) and \( \Delta \Xi_{i,m} = \frac{2\pi}{N_t} \).
Table 1. Summary of the symbols in the system model.

| Symbols          | Meaning                                                                 |
|------------------|-------------------------------------------------------------------------|
| \[N\]            | Set of \(n_s\)                                                          |
| \(n_m\)          | Index of sensor                                                        |
| \((r_n, \psi_n)\) | Coordinates of \(n_s\)                                                  |
| \((A_s, \varphi_0)\) | Coordinates of \(AP\)                                                  |
| \(B(\Theta_{i,m})\) | Beampattern of BSS                                                      |
| \(N_l\)          | Amplitude of \(B(\Theta_{i,m})\)                                       |
| \(\Theta_{i,m}\) | Steering angle of \(i\)-th beam                                       |
| \(\varphi_n(\varphi)\) | Local Azimuth angle                                                    |
| \(\Xi_{i,n}\)    | Set of \(s^k\)                                                         |
| \(S\)            | Index of active sensor                                                  |
| \(z_k\)          | Data symbol                                                            |
| \(M^k\)          | Set of \(m^k_m\)                                                       |
| \(m^k_m\)        | Neighbor sensors of \(s^k\)                                            |
| \(P_m\)          | Transmission power                                                     |
| \(\Gamma_m(\varphi_0)\) | Distance between \(m_m\) and \(AP\)                                  |
| \(d_{m}(\varphi_0)\) | Operating wavelength                                                  |
| \(\lambda\)      | Wireless channel                                                       |
| \(\hat{B}(\Theta_{i,m}, \Omega_m)\) | Beampattern with \(\Omega_m\)                                         |
| \(\Omega_m\)     | Random deviation angle                                                 |
| \(\Theta_M\)     | Set of \(\Theta_{i,m}\)                                               |

Let us state that one of the active source sensors, \(s^k \in S = \{s^1, \ldots, s^K\}\), \(K \ll N_s\), needs to transmit the data symbol \(z^k \in \mathbb{C}\), being satisfied with \(E[z^k] = 0, E[z^k]^2 = 1\), and \(E[z^k \neq z^{k'}] = 0\) for \(k \neq k'\), in the direction of \(AP\). To establish the direct transmission between \(s^k\) and \(AP\) without considering a multi-hop strategy, the scheme of the CB is introduced to coherently combine beams of \(M^k\) at \((A_s, \varphi_0)\), where \(M^k = \{m^k_1, \ldots, m^k_M\}\) is satisfied with the condition of \(\cup_{k=1}^K M^k = \mathbb{N}\) and \(M^k \cap M^{k'} = \emptyset\) for \(k \neq k'\), and its elements are within the coverage radius \(R\) of \(s^k\). From here, the superscript \(k\) is omitted to pursue concise representation. As the preparatory step of the CB, each sensor selects the beam that minimizes \(|\varphi_m(\varphi_0) - \Theta_{i,m}|\). Afterward, \(s\) shares \(z\) with \(M_m\) and then \(m_m\) broadcasts the data signal \(z\sqrt{P_m}e^{-jr_m(\varphi_0)}\) through its beam [41]. Here, \(P_m\) is the transmission power of \(m_m\), \(\Gamma_m(\varphi_0) = -\frac{2\pi}{\lambda}d_{m}(\varphi_0)\) is the closed loop initial phase for the carrier synchronization of \(M_m\), \(d_{m}(\varphi_0) = \sqrt{A^2 + (r_m)^2 - 2Ar_m\cos(\varphi_0 - \psi_m)}\) is the Euclidean distance between \(m_m\) and \(AP\), and \(\lambda\) is the wavelength of the operating frequency.

Let \(\sigma_m \sim \exp\{N(0, \sigma^2_m)\}\) denote the time-invariant and log-normal wireless channel between \(m_m\) and \(AP\) [59,60]. When the far-field condition \((A \gg r_m)\) is applied, the received signal at \(AP\) is given as

\[
y(\varphi|\Theta_M, \Omega_M) = z \sum_{m_m \in M} \sqrt{P_m}r_m \hat{B}(\Theta_{i,m}, \Omega_m) + n, \tag{2}
\]

where \(\hat{B}(\Theta_{i,m}, \Omega_m)\) is the radiation pattern with \(\Xi'_{i,m} = \left[\frac{\pi}{\pi M} + \Theta_{i,m} + \Omega_m + \frac{\pi}{\pi M} + \Theta_{i,m} + \Omega_m\right]\), \(\Omega_m \sim U(-\pi, \pi)\) is the random deviation angle due to the irregular surface where the sensors are mounted, and \(\Omega_M = [\Omega_1, \ldots, \Omega_M] \in [-\pi, \pi]_M\) and \(\Theta_M = [\Theta_{i,1}, \ldots, \Theta_{i,M}] \in \mathbb{R}\).
$[-\pi, \pi]^M$ represents the deviation and steering vector of $M$, respectively. Moreover, the received SNR is also given as

$$F(\Theta_M) = \frac{|y(\phi_0, \Theta_M, \Omega_M) - n|^2}{\sigma_n^2}. \quad (3)$$

Figure 6a shows the simulated SNR with various values of $N_t$. As observed, there are considerable gaps between the curves of “ideal” and “practical”. Especially, with the increment of $N_t$, the difference becomes more distinct (e.g., when $M = 12$, the differences at $N_t = 3$ and at $N_t = 12$ are 8.8 dB and 18.6 dB, respectively). This can be explained by the fact that when the higher $N_t$ is equivalent to the higher directivity; this leads to the increased number of sensors which do not illuminate AP. From the above results, it is recognized that an efficient algorithm for beam switching is required for the SNR enhancement in our scenario.

3. Proposed Algorithm

To conduct the beam alignment toward $\phi = \phi_0$ efficiently, the combinatorial optimization problem constrained with the predefined threshold SNR $\zeta$, SNR improvement $\nu$, and iterations $\rho$ is introduced, and it is formulated as follows,

$$\Theta_M^{opt} = \arg \max F(\Theta_M^t), \quad (4)$$

where $\Theta_M^t = [\Theta_{M}^t, \cdots, \Theta_{M}^t]$ is the state vector, and the superscript $t$ denotes the current state. To obtain the global optimum of (4), an exhaustive search can be used. However, it imposes the high complexity of $O(N^M)$. Thus, the GS, a traditional heuristic search, is utilized to efficiently approach the solution of (4). As the GS basically depends on the greedy transition from the worse state $\Theta_M^{t-1}$ to the better state $\Theta_M^t$, and the probabilistic transition is not allowed for $\Delta F = F(\Theta_M^t) - F(\Theta_M^{t-1}) \leq 0$, it cannot guarantee that it will reach the global optimum. However, our goal is to achieve the predetermined SNR improvement using limited computing resources. Thus, the GS is recommended as the core of the proposed algorithm [61]. The specific description is given as follows.

Step 1: Initialization. As the first step of the algorithm, one of the active sensors, $s$, sets the control parameters of the algorithm, $\zeta$, $\nu$, and $\rho$ as the default values. These values are important to balance between SNR improvement and system complexity.

Step 2: Broadcasting. $s$ broadcasts a switching message to alert the following beam-switching event to the neighbor sensors.
Step 3: Beam Switching. After receiving the switching message, each sensor randomly selects one of the directional beams, being generated from its own BSS, with 
\[ i \sim U[1, \cdots, N_t] \] and sends a selected message to \( s \).

Step 4: Data Sharing. After collecting the selected messages from the neighbor sensors, \( s \) shares its transmission data with them. When each of the sensors receives the data, it sends a shared message to \( s \).

Step 5: Sounding. (1) After collecting the shared messages from the neighboring sensors, \( s \) with \( M \) transmits a sounding message with the shared data through the CB. Here, it is assumed that \( s \) and \( M \) are synchronized. \( AP \) measures \( F(\Theta^t_M) \) and feeds it back to \( s \). (2) If \( F(\Theta^t_M) \) is larger than the predetermined threshold SNR, \( \zeta \), or \( F(\Theta^t_M) - F(\Theta^{t-1}_M) \geq \nu \) is met, then go to Step 7 directly.

Step 6: Updating. If \( F(\Theta^{t-1}_M) \) is available, \( s \) makes the decision for either the acceptance or rejection of the state transition. If it is not available, then go back to (1) of Step 2. When the transition is accepted, \( F(\Theta^{t-1}_M) \) is replaced with \( F(\Theta^t_M) \). Then, return to Step 2, and \( s \) repeats from Step 2 to Step 6 during \( \rho \) iterations.

Step 7: Abort. Check whether all iterations have stopped or \( F(\Theta^t_M) \geq \zeta \) or \( F(\Theta^t_M) - F(\Theta^{t-1}_M) \geq \nu \) is met. If either of these conditions are true, \( s \) broadcasts an abort message, and uses the set of beams having \( \Theta^t_M (t' \gg t) \) for the future data transmission.

4. Simulations and Experiments

To evaluate the proposed scheme, this section provides the simulation results of the received SNRs and the complexity. Furthermore, to verify whether the proposed algorithm is applicable in practical sensors [62], the execution time and the current dissipation in an MCU are investigated. Here, note that the MCU performance experiment is conducted for the feasibility of our algorithm in a practical embedded environment. The wireless link performance is only verified by MATLAB simulations. As illustrated in Figures 7 and 8, and Table 2, an experiment setup is composed of a STM32F4-Discovery, an Universal Asynchronous Receiver Transmitter (UART) module, and an Atmel power debugger. The STM32F4-Discovery is a MCU with a 32-bit ARM Cortex-M4 and an FPU core, 1 Mbyte of flash memory, and 192 Kbytes of RAM. In addition, the UART module and the Atmel power debugger are exploited to forward environmental parameters of the WSN, being generated by MATLAB, to the MCU and to measure the current consumption of the MCU, respectively.

Table 2. Summary of simulation setup and experiment configuration.

| Simulation Setup | Experiment Configuration |
|------------------|--------------------------|
| Parameter        | Value | Parameter | Value | Device | Function |
| \( M \)          | 12    | \( R \)    | 1\( \lambda \) | STM32F4-Discovery | MCU |
| \( \varphi_0 \)   | 0     | \( \eta \)  | 12    | UART Module | Data transmission |
| \( \sigma^2_a \)  | 0.2   | \( \rho \)  | \( 10^5 \) | Atmel Power Debugger | Power measurement |
1. Generate the position of each node [MATLAB].
2. Generate the beam direction of each node [MATLAB].
3. Generate the channel state of each node [MATLAB].
4. Generate the beam gain of each node [MATLAB].
5. Define the experiment condition (number of node and threshold SNR) [MATLAB].
6. Import the parameters and the experiment condition generated from step 1 to step 6 [MCU].
7. Measure the power consumption and the execution time [MCU].

Prior to the detailed studies, the assumptions of the system and algorithm are given as follows. Twelve sensors (M = 12) are uniformly distributed over a disk of radius $\tilde{R} = 1\lambda$, and the beams aiming at $\psi_0 = 0$ are selected. $P_m$ is equally set as $\sigma_n^2\eta/M$, where the power budget $\eta$ is equal to 20 dB, and $\sigma_n^2$ is set to 0.2. Finally, the parameter of $\rho$ is fixed to $10^5$. As shown in Figure 6b, setting $\rho > 10^5$ can increase the possibility of approaching the global optimum. However, this behavior would lead to excessive power consumption and overhead overwhelming the SNR improvement.

Figures 9 and 10 illustrate the simulated results with respect to the received SNRs and the number of the iterations. In Figure 9, it is observed that our algorithm provides a significant SNR improvement (e.g., when $\zeta = 50$ dB and $\nu = 16$ dB, 8.1 dB, 11.4 dB, and 14.1 dB at $N_t = 3$, $N_t = 6$, and $N_t = 12$, respectively). Additionally, as seen in Figure 10, the lower $\zeta$ and $\nu$ are set, the easier it is for the algorithm to increase the SNR within the relative smaller iterations. Interestingly, this phenomenon is also observed when $N_t$ is higher, due to the fact that the power concentration by the directional beams surpasses the possibility of the absence of sensors in the CB. In addition, Figure 11 verifies that the proposed algorithm
requires the following execution time (=operating cycles/MCU clock (M)) between 0.2 s and 7.2 s. From Figure 12a, it is also confirmed that the supplied current into the MCU is marginally increased (averagely, 11.23%) even when the proposed algorithm is executed under the worst conditions of $\zeta = 50 \text{ dB}$, $\nu = 16 \text{ dB}$, and $N_t = 3$. Finally, Figure 12b shows that as $\Omega$ is increased, the dissipated current is conversely decreased. This tendency occurs because the reduction in the execution time is more dominant than the increase in the supplied current. Considering the above results, it is concluded that the proper combinations of $N_t$ and $M$ result in the acceptable execution time and current dissipation even when the high values of $\zeta$ and $\nu$ are configured (e.g., when $N_t = 12$, $\zeta = 46 \text{ dB}$, $\nu = 16 \text{ dB}$, and $\Omega = 168 \text{ MHz}$ are set, the execution time and the dissipated current is $0.26 \text{ s}$ and $0.023 [A \times s]$, respectively).

**Figure 9.** The simulated SNRs of the proposed algorithm versus $\zeta$ when $\nu$ is set as (a) 2 dB, (b) 4 dB, (c) 8 dB, and (d) 16 dB, respectively.
Figure 10. The simulated number of the iterations of the proposed algorithm versus $\zeta$ when $\nu$ is set as (a) 2 dB, (b) 4 dB, (c) 8 dB, and (d) 16 dB, respectively.

Figure 11. The measured operating cycles of the proposed algorithm versus $\zeta$ when $M$ is set as 168 MHz, and $\nu$ is set as (a) 2 dB, (b) 4 dB, (c) 8 dB, and (d) 16 dB, respectively.
Figure 12. (a) The supplied current versus $M$ when the proposed algorithm is executed (execution mode) or not (normal mode). (b) The dissipated current (=supplied current $\times$ execution time) versus $M$.

5. Conclusions

In this paper, it is assumed that each sensor in a WSN is equipped with a BSS. The received SNR at the desired AP is investigated to bolster the validity of the motivation in this paper and presented the optimization problem of (4). An algorithm is also proposed to solve this problem in an efficient manner. The simulation and experimental results showed that with the proper combination of the given parameters, our algorithm can increase the received SNR substantially with low computing resources and energy consumption. In future work, a reinforcement learning-based beam-switching algorithm will be designed to autonomously adjust to the complex and unpredictable propagation channel.

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Abbreviations

The following abbreviations are used in this manuscript:

- WSN: Wireless Sensor Network
- AP: Access Point
- CB: Collaborative Beamforming
- BSS: Beam-Switching Structures
- SNR: Signal-to-Noise Ratio
- GS: Greedy Search
- RF-MEMS: Radio-Frequency Micro-Electromechanical Systems
- GPS: Global Positioning System
- MCU: Micro Controller Unit
- UART: Universal Asynchronous Receiver Transmitter
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