Secure Low-power IoT Uplink Communication via Unsupervised Signal Alignment

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***Abstract*—This paper considers the problem of unsupervised detection in IoT uplink communication over fading channels with multiple antennas at the access point (AP). Instead of requiring long training sequences and coordination between the sensor nodes for training or power control, this work proposes using a simple transmission scheme consisting of repetition coding followed by random interleaving together with a signal alignment strategy at the AP. The key innovation is that pseudo-random (de-)interleaving is used here to simultaneously align the signal of interest, misalign (scramble) the interfering signals, *and* provide physical layer security. The combination allows reliable detection of the signal of interest at the AP via canonical correlation analysis, even under low-power / high interference conditions. The end-to-end approach provides rigorous recovery guarantees, allows for secure communication between the sensor nodes and the AP, and is computationally cheap. Simulations demonstrate the efficacy of the proposed approach compared to widely used multiplexing methods.**

***Index Terms*—IoT, low-power communication, physical layer security, multiple-input-multiple-output (MIMO), uplink, Canonical correlation analysis (CCA).**

I. Introduction

For over 20 years, we have witnessed growing interest in wireless sensor networks (WSNs) [1], a trend which has recently reached new hights with the emergence of cheap low-power Internet of Things (IoT) devices that can function as ubiquitous sensor nodes. The growing popularity of IoT networks is driven by the wide variety of applications that range from environmental and factory monitoring, to military surveillance, health care, and home automation. In these diverse application domains, a number of low-cost IoT nodes are deployed over a particular region with the goal of collecting information and sending it, in analog or digital form, to an access point (AP) for further processing [2].

The tremendous increase in the number of wirelessly-connected sensors has motivated the use of multiple receive antennas at the AP [3], thereby enabling bandwidth-efficient transmission schemes that allow multiple sensors to transmit simultaneously over the same time-frequency resource block. In this context, a key question is how to reliably decode low-power sensor transmissions at the AP. Existing works [3]–[8] assume that accurate channel state information (CSI) between the sensors and the AP is available. This requires long training sequence transmission and some degree of coordination between the IoT nodes for synchronization and/or power control, which are beyond the capabilities of low-cost low-power IoT devices.

The goal of this paper is to propose a low-complexity approach that enables reliable detection of low-power IoT transmissions at the AP, without any coordination between the IoT nodes – while also providing a certain level of physical layer security. The paper shows that this is possible using a simple transmission protocol that allows seamless and secure communication between the IoT nodes and the AP. The key idea is as follows: each IoT node merely transmits its signal twice followed by scrambling the two signal blocks using a pseudo-random permutation code, determined by the node's identification code. Under the assumption that different sensors have different permutation patterns, de-interleaving the received signal at the AP and utilizing the repetition structure allows forming one de-interleaved matrix pair for each IoT transmitter in which the given transmitter's signal is aligned (common between the two matrix views), and all interfering IoT signals are misaligned across the two views. Applying canonical correlation analysis (CCA) on each pair separately, this paper shows that the aligned signal can be reliably decoded at low SNR, in an unsupervised manner, without any other constraints on the transmitted waveforms. The approach even works for analog modulation.

In addition to superior communication performance, the use of pseudo-random scrambling means that if an eavesdropper does not know a device's pseudo-random generator, it is very difficult (if not practically impossible) to align the two signal views, as the number of possible permutations is combinatorial and practically intractable even for moderate interleaver depths. The proposed approach is theoretically backed by identifiability proof and performance analysis established earlier by the authors [9] in the context of another application. The key innovation here is the judicious use of scrambling and descrambling to align the signal of interest at the receiver and misalign the interfering signals, thereby reducing the decoding complexity dramatically, as well as providing a level of physical layer security at the same time. Numerical results reveal the superior performance of the proposed approach in reliably decoding the sensor signals, analog and/or digital, relative to the state-of-the-art approaches.

CCA is a powerful and widely-used data analysis tool that has previously found many applications in signal processing and wireless communications, including equalization [10],

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blind source separation [11], [12], multi-view learning [13]–[15], and more recently cell-edge user detection [9]. From the computational perspective, CCA is practically appealing as the CCA problem admits a simple algebraic solution via eigendecomposition.

The rest of the paper is organized as follows. Section II describes the system model and defines the problem. The proposed transmission protocol is presented in Section III, while Section IV presents the proposed detector. Simulation results are provided in Section V, and conclusions are drawn in Section VI.

II. System Model and Problem Statement

Consider a wireless sensor network comprising K single-antenna IoT sensors and an AP equipped with M antennas, as shown in Fig. 1. The k-th sensor transmits its data, $\{\mathbf{s}_k[n]\}_{n=1}^N$, at the n-th time index to the AP, where without loss of generality we assume $\mathbb{E}[|\mathbf{s}_k[n]|^2] = 1$, $\forall n \in [N] := \{1, \cdots, N\}$ and $k \in [K] = \{1, \cdots, K\}$. Let $\mathbf{h}_k = \sqrt{\alpha_k}\mathbf{z}_k$ be the vector representing the fading channel between the k-th sensor and the AP. The entries of $\mathbf{z}_k$ represents the small scale fading coefficients, and are assumed to be independent and identically distributed (i.i.d) Gaussian random variables with zero mean and variance $1/M$, i.e., $\mathbb{E}[\|\mathbf{z}_k\|_2^2] = 1$. The term α_k accounts for the large scale fading coefficient (path-loss) between the k-th sensor and the AP. Towards this end, the discrete time baseband-equivalent model of the received signal at the AP, $\mathbf{y} \in \mathbb{C}^M$, from all K sensors is given by

$$\mathbf{y}[n] = \sum_{k=1}^{K} \beta \mathbf{h}_k \mathbf{s}_k[n] + \mathbf{w}[n], \tag{1}$$

where $\mathbf{s}_k[n] \in \mathbb{C}$ is the k-th IoT node observations received at the AP at the n-th instant, and β stands for the transmit power term which is assumed to be fixed across all sensors. The term $\mathbf{w}[n]$ represents the additive noise vector with i.i.d elements drawn from Gaussian distribution with zero mean and variance σ^2.

Assuming that the AP collects the sensors data over N snapshots, the received signal in (1) can be expressed in more compact form as

$$\mathbf{Y} = \sum_{k=1}^{K} \beta \mathbf{h}_k \mathbf{s}_k^T + \mathbf{W}, \tag{2}$$

The main goal is to reliably decode the data of the K sensors $\{\mathbf{s}_k\}_{k=1}^K$, given the received measurements $\{\mathbf{y}[n]\}_{n=1}^N$ at the AP. Prior works [3], [6]–[8] rely on the assumption that accurate channel state information (CSI) is available at the AP which limits their use in practical situations. We will next show that, via a simple transmission strategy employed at the sensors together with an unsupervised detection method used at the AP, the sensors' signals can be reliably decoded even at low SNR without any CSI.

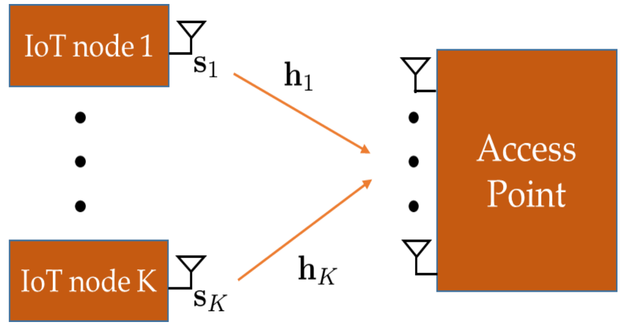

Fig. 1: System Model

III. Proposed Transmission Strategy

In this section, we will propose a simple transmission strategy for the sensors so that their signals can be decoded at the AP. The transmission scheme consists of two steps; repetition followed by interleaving. First, the k-th sensor forms two blocks by simply sending its signal $\mathbf{x}_k \in \mathbb{C}^{N/2}$ twice at very low power. Upon forming the two back-to-back blocks, i.e., $[\mathbf{x}^T, \mathbf{x}^T]$, the k-th sensor pseudo-randomly permutes the N symbols (samples for analog transmission). The transmitted signal, $\mathbf{s}_k$, from the k-th sensor after repetition and interleaving can be written as

$$\mathbf{s}_k = \mathbf{\Pi}_k \begin{bmatrix} \mathbf{x}_k \\ \mathbf{x}_k \end{bmatrix}, \; \forall k \in [K], \tag{3}$$

where $\mathbf{\Pi}_k \in \mathbb{R}^{N \times N}$ is a pseudo-random sensor-specific permutation matrix. We assume that different sensor nodes have different permutation matrices. Given that there are $N!$ possible permutation matrices, even with modest N, e.g., $N = 128$, there is a huge number of permutation matrices, making de-interleaving close to impossible unless one knows the true permutation matrix of the sensor of interest. The permutation matrix of the k-th sensor can be generated using its unique ID, which is assumed to be known at the AP, $\forall k \in [K]$.

Remark 1. *At a first glance, the proposed repetition scheme can be viewed as spreading each sensor signal with spreading gain equal to two. However, dealing with this situation as if it were CDMA will not work as well as our approach because of the very limited spreading gain and the sensitivity of CDMA to near-far power imbalance – inevitable in the absence of coordinated power control due to the fading-induced variations in the received signal power of the different IoT nodes at the AP. Near-far power imbalance significantly impacts CDMA performance [16] as we will also verify in the experiments.*

Upon plugging (3) in (2), the received signal at the AP can be written in more compact form as

$$\mathbf{Y} = \mathbf{H}\mathbf{S}^T + \mathbf{W}, \tag{4}$$

where $\mathbf{W} \in \mathbb{C}^{M \times N}$ is the noise term, $\mathbf{H} = [\mathbf{h}_1, \cdots, \mathbf{h}_K] \in \mathbb{C}^{M \times K}$ holds in its columns the channel vectors of the K

sensors (the transmit power terms have been absorbed in the channel vectors for simplicity), and the matrix $\mathbf{S} \in \mathbb{C}^{N\times K}$ has in its columns the corresponding sensor signals (after repetition and permutation), i.e.,

$$\mathbf{S} = \left[\mathbf{\Pi}_1 \begin{bmatrix}\mathbf{x}_1\\ \mathbf{x}_1\end{bmatrix}, \quad \ldots \quad, \mathbf{\Pi}_K \begin{bmatrix}\mathbf{x}_K\\ \mathbf{x}_K\end{bmatrix}\right], \tag{5}$$

It is worth-noting that the repetition structure in the proposed transmission protocol can be utilized for synchronization purposes at the AP. In particular, we can use the proposed algorithms in [9], [17], with some modifications, to find the start time of the different sensors signals. However, due to space limitations, we will leave the asynchronous setup for the journal version of this work. We will next present a low complexity method that can reliably decode the sensor signals $\{\mathbf{s}_k\}_{k=1}^K$, at low SNR, in an unsupervised manner.

IV. Proposed Detector

In order to reliably decode the low-power sensor signals at the AP, we use canonical correlation analysis (CCA). In its simplest form, CCA is a statistical learning tool that aims at finding two linear combinations of random vectors $\mathbf{y}_1 \in \mathbb{C}^{M_1}$ and $\mathbf{y}_2 \in \mathbb{C}^{M_2}$ such that the resulting pair of scalar random variables is maximally correlated [18], [19]. Assuming that we are given N realizations of the random vectors $\mathbf{y}_1$ and $\mathbf{y}_2$, i.e., $\mathbf{Y}_\ell = [\mathbf{y}_\ell[1], \cdots, \mathbf{y}_\ell[N]] \in \mathbb{C}^{M_1\times N}$ for $\ell = 1, 2$, the CCA problem can be posed as [19],

$$\min_{\mathbf{q}_1,\mathbf{q}_2} \|\mathbf{Y}_1^H\mathbf{q}_1 - \mathbf{Y}_2^H\mathbf{q}_2\|_2^2 \tag{6a}$$

$$\text{s.t.} \quad \mathbf{q}_\ell^H\mathbf{Y}_\ell\mathbf{Y}_\ell^H\mathbf{q}_\ell = 1, \quad \ell = 1, 2, \tag{6b}$$

The above problem is referred to as the distance minimization formulation of CCA. It seeks to find two canonical vectors $\mathbf{q}_1 \in \mathbb{C}^{M_1}$ and $\mathbf{q}_2 \in \mathbb{C}^{M_2}$, such that Euclidean distance between the resulting vector realizations is minimized. An equivalent formulation of (6), in the two views case, is to look for a shared low-dimensional representation $\mathbf{g} \in \mathbb{C}^N$ of the two data views $\mathbf{Y}_1$ and $\mathbf{Y}_2$. This can be written as

$$\min_{\mathbf{g},\mathbf{q}_1,\mathbf{q}_2} \sum_{\ell=1}^{2} \|\mathbf{Y}_\ell^H\mathbf{q}_\ell - \mathbf{g}\|_2^2, \tag{7a}$$

$$\text{s.t.} \quad \|\mathbf{g}\|_2^2 = 1, \tag{7b}$$

which is called the maximum variance (MAXVAR) formulation of CCA [20]. From the computational point of view, problem (7) admits a relatively simple algebraic solution. In particular, the optimal solution $(\mathbf{q}_1^\star, \mathbf{q}_2^\star, \mathbf{g}^\star)$ of (7) can be obtained via eigendecomposition of a matrix that involves three correlation matrices and two small matrix inversions.

We recently discovered a new interpretation of CCA from an algebraic point of view [21]. That is, given two multi-antenna signals with strong components that are different across the two views, and a weak shared (common) component, CCA will recover the common component regardless how strong the individual components are. We also established a performance analysis which shows that reliable detection of the common signal via CCA is possible at low SNR/SINR [9].

Building upon these insights, it is not difficult to see that de-interleaving the received signal at the AP using one of the matrices $\{\mathbf{\Pi}_k\}_{k=1}^K$, will produce two signal views that share only one common component corresponding to the signal of that particular sensor. All other sensors will be randomly permuted, and thus will not align with the two-fold signal blocks. To see this, let us multiply each row of (2) by the permutation matrix associated with the i-th sensor, $\mathbf{\Pi}_i$, to obtain

$$\mathbf{Y}^{(i)} = \mathbf{H}\left[\mathbf{\Pi}_i^T\mathbf{\Pi}_1\begin{bmatrix}\mathbf{x}_1\\ \mathbf{x}_1\end{bmatrix}, \cdots, \begin{bmatrix}\mathbf{x}_i\\ \mathbf{x}_i\end{bmatrix}, \cdots, \mathbf{\Pi}_i^T\mathbf{\Pi}_K\begin{bmatrix}\mathbf{x}_K\\ \mathbf{x}_K\end{bmatrix}\right]^T + \mathbf{W}^{(i)}, \tag{8}$$

where $\mathbf{W}^{(i)} := \mathbf{W}\mathbf{\Pi}_i$ and $\mathbf{\Pi}_i^T\mathbf{\Pi}_i = \mathbf{I}$, $\forall i \in [K]$. Define $\mathbf{\Pi}_{ij} := \mathbf{\Pi}_i^T\mathbf{\Pi}_j$ as the resulting permutation matrix, and $[\mathbf{x}_i^{(1)T}, \mathbf{x}_i^{(2)T}]^T = \mathbf{\Pi}_{ij}[\mathbf{x}_i^T, \mathbf{x}_i^T]^T$, where $i, j \in [K]$ and $i \neq j$. Then, it follows that by constructing the two signal views $\mathbf{Y}_1^{(i)} := \mathbf{Y}(:, 1:N/2)$ and $\mathbf{Y}_2^{(i)} := \mathbf{Y}(:, 1+N/2:N)$[1], $\forall i \in [K]$, we obtain

$$\mathbf{Y}_1^{(i)} = \mathbf{H}\left[\mathbf{x}_1^{(1)T}, \cdots, \mathbf{x}_i^T, \cdots, \mathbf{x}_K^{(1)T}\right]^T + \mathbf{W}_1^{(i)}, \tag{9}$$

$$\mathbf{Y}_2^{(i)} = \mathbf{H}\left[\mathbf{x}_1^{(2)T}, \cdots, \mathbf{x}_i^T, \cdots, \mathbf{x}_K^{(2)T}\right]^T + \mathbf{W}_2^{(i)}, \tag{10}$$

where $\mathbf{W}_\ell^{(i)}$ is the resulting noise after partitioning $\mathbf{W}^{(i)}$, for $\ell = 1, 2$. From (9) and (10), it is obvious that the two signal blocks share a unique common component, namely the span of $\mathbf{s}_i$ that conveys the i-th IoT node transmission. Upon defining the matrix $\mathbf{B}_\ell^{(i)} = [\mathbf{x}_1^{(1)T}, \cdots, \mathbf{x}_i^T, \cdots, \mathbf{x}_K^{(1)T}] \in \mathbb{C}^{N/2\times K}$, $\forall i \in [K]$ and $\ell = 1, 2$, we have the following result.

Theorem 1. *In the noiseless case, if the matrices $\mathbf{B}_\ell^{(i)} \in \mathbb{C}^{N/2\times K}$, for $\ell \in \{1, 2\}$, and $\mathbf{H} \in \mathbb{C}^{M\times K}$ are full column rank, then the optimal solution $\mathbf{g}^\star$ of problem* (7) *is given by $\mathbf{g}^\star = \gamma\mathbf{s}_i$, where $\gamma \in C$, $\gamma \neq 0$ is the scaling ambiguity.*

Proof. The proof follows from Theorem 1 in [21]. ☐

Note that satisfying the full rank condition on the matrix $\mathbf{B}_\ell^{(i)}$ requires half the packet length to be greater than the number of sensors and the transmitted sequences to be linearly independent, for $i = 1, 2$. Both conditions can be easily satisfied with modest N since the different sensors' transmissions are independent. Further, to satisfy the full rank condition on the channel matrix $\mathbf{H}$, we need the number of antennas to be greater than the number of IoT sensors and the channel vectors of the different IoT sensors to be linearly independent. The latter will be satisfied with probability one if the channel vectors are drawn from a jointly continuous distribution.

It is worth pointing out that the random permutation step in the proposed transmission protocol possesses several appealing features. First, it provides secure communication between all the sensor nodes and the AP, since it is impossible to

[1] MATLAB notation is used here, where $\mathbf{Y}_1^{(i)} := \mathbf{Y}(:, 1:N/2)$ contains all the rows of $\mathbf{Y}$ and a subset of columns (from the first one to the $\frac{N}{2}$ column).

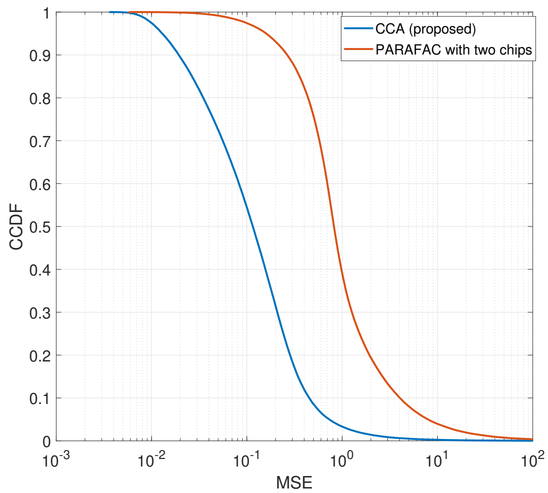

Fig. 2: CCDF of the MSE, $M = 32,\ K = 20$, analog signals for all sensors. Average MSE for CCA and PARAFAC is 0.1 and 1, respectively.

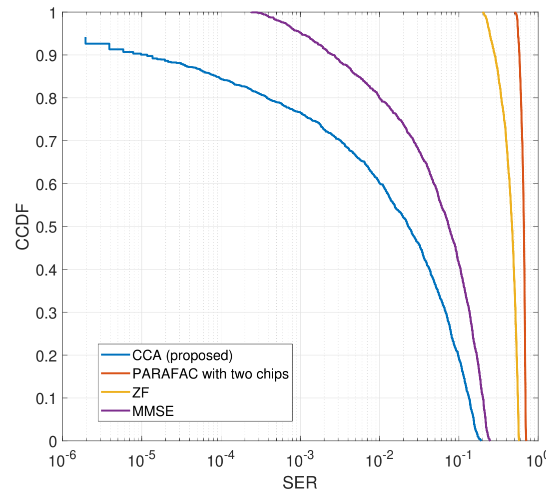

Fig. 3: CCDF of the SER, $M = 32\ K = 32$, QPSK signals for all sensors. Average SER for CCA and MMSE is 0.019 and 0.074, respectively.

decode the sensor data without knowing $\{\mathbf{\Pi}_k\}_{k=1}^{K}$. Second, it significantly reduces the receiver complexity as opposed to the case with multi-dimensional common subspace [9] because the latter requires an additional stage to unravel the common signals form the resulting mixture, where depending on the adopted modulation and coding scheme, different methods can be employed to recover the original signals. However, these methods are complex to implement in practice, especially for higher-order QAM signals (and do not work for multiple analog signals). Finally, it does not impose any assumptions on the structure of the transmitted waveform of any node – waveforms can be different across all nodes.

V. Experimental Results

To assess the performance of the proposed CCA approach, we have simulated a dense uplink scenario in a wireless sensor network with 20 IoT sensor nodes and an AP equipped with $M = 32$ antennas. The sensor nodes are randomly dropped from 10 to 60 meters from the AP. We set the carrier frequency to 28 GHz, the transmission power to 0.5 mWatt, the thermal noise to -174 dBm/Hz, the bandwidth to 10 MHz, and the packet size to 512 symbols. We assume a rich scattering environment where the entries of the channel vectors are independent and identically distributed (i.i.d) random variables drawn from a complex Gaussian distribution with zero mean and variance $1/\sqrt{M}$. Also, a free-space path-loss model is used to model the path loss between the sensors and the AP.

The average received SNR of the sensors ranges from 4 dB to 20 dB, according to their distances from the AP. In our transmission protocol, after block repetition, the resulting signal block is randomly interleaved using a unique seed for each sensor. We conducted 10^4 Monte-Carlo simulations, each time changing the sensor locations, transmitted signals, channel vectors, and noise.

To benchmark the proposed method's performance, we use parallel factor analysis (PARAFAC), a tensor-based method that can handle the same problem if instead of simple packet repetition we spread each user's packets with two random chips (spreading gain = 2) [22]. We then normalize to the same average transmission power for a fair comparison to CCA with random interleaving. PARAFAC offers identifiability guarantees [22] – however, *unlike CCA*, PARAFAC is sensitive to near-far effects. To resolve the scaling ambiguity that is inherent to both CCA and PARAFAC, we assume that the first symbol of all the sensors' transmissions is known at the AP. Further, for digitally modulated signals, we implemented two widely-used multiuser detection methods, namely zero-forcing (ZF) and minimum mean squared error (MMSE). In particular, instead of repetition, we dedicated half of the packet length for pilots transmission to estimate the channel of each sensor, and the other half for payload data. This results in the same transmission rate for all methods.

In the first experiment, we assume that the transmitted signals from the sensors are real analog with each sample drawn from Gaussian distribution with zero mean and unit variance. Fig. 2 shows the complementary cumulative distribution function (CCDF) of the mean square error (MSE) obtained using CCA, and the MSE obtained using parallel factor analysis (PARAFAC). Fig. 2 demonstrates the remarkable performance of CCA over the tensor-based method. In particular, CCA can achieve an average MSE of roughly 10^{-1} which is approximately one order of magnitude lower than what is achieved by PARAFAC. CCA also has *much lower* complexity compared to PARAFAC – the latter also requires an extra stage to resolve the permutation ambiguity. More interestingly, at the low SNR region (5-percentile of the CCDF), 95% of the nodes can achieve less than 0.45 MSE using CCA as opposed to 8.5 for PARAFAC, so more than an order of magnitude improvement and the gap becomes even wider as the SNR decreases (the tails of the CCDF). This reflects how well our approach works at low SNR ranges.

We carried out another experiment with QPSK modulation for all sensors, with a full load scenario where the number of antennas is equal to the number of sensors, i.e., $M = K = 32$. Further, the packet size is set to 1024; each block has 512 symbols for CCA while for MMSE and ZF, we use 512 pilots for channel estimation. Fig. 3 demonstrates the superiority of the proposed approach relative to ZF, MMSE and PARAFAC. The CCDF curves shows that CCA attains an average of 0.019 SER which is way better than MMSE and ZF that achieve 0.074 and 0.5, respectively. Also note that both ZF and MMSE require channel estimation, and hence they are more complex to implement compared to CCA. Further, one can see from the CCDF curves in Fig. 3 that CCA can achieve less than 0.01 in 40% of the instances (total number of points 320000), while MMSE can achieve the same SER in only 20% of the instances.

VI. Conclusions

This paper has considered the problem of unsupervised detection in a wireless sensor network where low-power IoT sensors are transmitting observations to a multi-antenna AP. The proposed framework enables low-power and secure sensor communication with the AP, without need for any channel state information between the sensors and the AP. The proposed solution employs repetition coding followed by random scrambling: each sensor sends its signal twice at low power then randomly permutes the two-block signal using a a pseudo-random code. De-interleaving the received signal at the AP using one of the sensors' codes and folding the two signal blocks followed by applying CCA on the two constructed views, we have showed that even analog modulated sensor signals can be reliably estimated even at low SNR. The end-to-end proposed method is computationally cheap, mitigates the AP receiver complexity compared to other methods, and does not pose any structure on the transmitted waveforms from the sensors. Simulations have demonstrated the superiority of the proposed approach relative to the state-of-the-art methods.

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