Active Wireless Sensing:  
A Versatile Framework for Information 
Retrieval in Sensor Networks  

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Abstract  

Many existing information extraction schemes in sensor networks are based on in-network processing that requires information routing and coordination between nodes and incurs excess overhead in delay and energy consumption. In this paper, we describe a viable alternative and complementary approach – Active Wireless Sensing (AWS) – in which a Wireless Information Retriever (WIR) queries a select ensemble of nodes to obtain desired information in a rapid and energy-efficient manner. The basic architecture in AWS consists of: i) a WIR, equipped with an antenna array, interrogates the wireless sensors with wideband space-time waveforms, ii) the sensors modulate the acquired waveforms with their (possibly encoded) measured data and generate an ensemble response to the WIR’s interrogation signal, and iii) the WIR extracts the sensor data by exploiting the space-time characteristics of the resulting multipath sensing channel. We propose a canonical family of sensing configurations that represent a simple abstraction of spatial correlation in the signal field or the nature of local cooperation in the network. The concept of source-channel matching is introduced in which the spatio-temporal resolution is adapted to the spatial scale of node correlation in the sensing configurations. Signaling strategies and associated receiver structures at the WIR are developed for different source-channel matched configurations. The performance of AWS is analyzed in different configurations both in terms of reliability and capacity of information retrieval. In particular, coherent source-channel matching, in which sub-ensembles of sensors with highly correlated data transmit in a phase-coherent fashion, is shown to offer significant gains in energy efficiency as well as capacity. The analysis is supported with realistic numerical results.  

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I. INTRODUCTION

Wireless sensor networks promise an unprecedented ability to monitor the physical environment through spatially distributed devices that can sense the environment in a variety of modalities and communicate with each other in a wireless fashion [1]–[3]. Inference of relevant information about the sensed signal field, such as the sensor data or some summary statistic, is one of the primary applications of sensor networks. Extracting relevant information with minimal expenditure of network resources, especially energy of battery-powered nodes, is one of the primary constraints in the design and operation of sensor networks. It is widely recognized that the processes of sensing and communication should be jointly optimized for energy efficiency.

The original vision of a flat, ad hoc communication topology for sensor networks has generated a lot of interest in in-network processing where either the network as a whole obtains a consistent estimate or consensus of desired information (see, e.g., [4], [5]), or the distributed information is routed to a decision center (see, e.g., [6]). In both cases, an underlying assumption is that information is diffused through the network in a multi-hop fashion to conserve communication energy. However, energy analysis of in-networking processing, such as consensus algorithms [4], [5], [7], ignores the energy overhead for establishing the required networking protocols for multi-hop routing. In addition, in-network processing also incurs excess delay that may be unacceptable in time-critical tasks, such as rapid detection of events or objects. For example, it has been shown that for a network with \( n \) nodes, consensus algorithms require \( O(n^{3/2} \log(n)) \) iterations to guarantee convergence with high probability [5]. Such excess energy consumption and latency can be quite significant, especially given the fact that information processing in a sensor network is dictated by the time-varying spatio-temporal characteristics of the sensed signal field and, as a result, information routing protocols may have to be updated as a function of the field characteristics. Finally, and most importantly, engineering large-scale sensor networks with a completely ad hoc topology has been very challenging to date [8]. Thus, there is renewed interest in investigating other network topologies, such as mesh networks, that combine the structure of a cellular topology with the flexibility of an ad hoc topology in a controlled fashion.

In [9], [10] we proposed an alternative and complementary approach to in-network processing – Active Wireless Sensing (AWS) – in which a Wireless Information Retriever (WIR) queries a select ensemble of nodes to obtain desired information in a rapid and energy-efficient manner. AWS has two primary attributes: i) the sensor nodes are “dumb” in that they have limited computational ability but have relatively sophisticated communication front-ends, and ii) the WIR is computationally powerful and is equipped
Fig. 1. Active Wireless Sensing. (a) Basic communication architecture. (b) Computation of sufficient statistics at the WIR.

with a multi-antenna antenna array. The basic architecture in AWS is illustrated in Fig. 1 and consists of: i) the WIR interrogates a select ensemble of wireless sensors with wideband space-time waveforms, ii) the sensor modulate their acquired temporal waveforms with (possibly encoded) measurement data, and iii) the WIR extracts sensor data from the ensemble response by exploiting the differences in the space-time characteristics of individual sensor responses. Thus, the computational burden is shifted to the WIR. Furthermore, the WIR can remotely “program” the sensor ensemble for different information retrieval tasks, such as field estimation or event detection.

Technological advances in agile radio frequency (RF) front-ends and reconfigurable antenna arrays provide another key motivation for AWS. WIRs equipped with agile RF transceivers could interrogate the sensor network at varying spatio-temporal resolutions, thereby enabling rapid learning of the spatio-temporal characteristics of the sensor field [11]. In this regard, the AWS framework exploits the advanced functionality afforded by agile, wideband RF front-ends in hierarchical architectures in sensor networks where the sensor nodes directly communicate with a base station or access point; see, e.g., [12]–[16]. Such WIRs could also be integrated with strategically located access points in mesh networks for network state monitoring and control. The basic methodology in AWS also shares commonality with recent research in waveform agility for communication and sensing; see, e.g., [17].

The basic concept of AWS is inspired by an intimate connection with communication over space-time multiple antenna (MIMO) wireless channels in a multipath environment: sensor nodes act as active scatterers and generate a multipath signal in response to WIR’s interrogation signal. A key idea behind AWS is to separate multiple sensor responses by resolving the multipath signals in angle and delay at a resolution commensurate with the spatio-temporal signal space, as illustrated in Fig. 1. This is facilitated by a virtual representation of wideband space-time wireless channels that we have developed in the past several years [18]–[21]. In particular, the virtual representation yields a natural partitioning of sensor
responses in angle-delay and provides a mathematical framework for studying fundamental performance limits of AWS at different spatio-temporal resolutions afforded by agile RF front ends.

AWS is similar, in terms of the underlying physics, to the concept of Imaging Sensor Nets that has been independently proposed recently [22], [23]. However, the basic underlying methodology in these works, inspired by radar imaging principles, is quite different and focuses on sensor localization and detection of spatially well-separated events. Our emphasis, in contrast, is on exploiting the capabilities afforded by agile RF front-ends for sensor information retrieval, and we exploit connections with recent developments in space-time wireless communications theory. We believe that these two related approaches provide complementary perspectives on information extraction in sensor networks and could be fruitfully cross-leveraged by exploring the connections between wideband radar imaging, wideband wireless communications, and waveform agility in the context of sensor networks.

The focus of this paper is on line-of-sight communication between the sensor ensemble and the WIR. Sec. II develops the basic communication architecture underlying AWS. At the highest spatio-temporal resolution, each angle-delay matched filter (MF) output in Fig. 1(b) is associated with a distinct angle-delay resolution bin in Fig. 1(a) which is occupied by a distinct sensor. The MF outputs in Fig. 1(b) are jointly processed at the WIR to retrieve sensor data. Sec. III presents canonical sensing configurations that form the basis of this paper and represent a simple abstraction of spatial correlation in the sensed signal field or the nature of local cooperation between sensor nodes. The sensor ensemble is partitioned into spatial coherence regions (SCRs), where the sensors in distinct SCRs transmit independent information whereas the sensors within each SCR send identical information (see also [13]). Sec. IV describes the signal processing at the WIR for information retrieval at the highest resolution for different sensing configurations and the corresponding probability of error is analyzed when the sensors transmit their measurements via uncoded BPSK modulation. Secs. V and VI discuss the receiver structures and analyze the probability of error for source-channel matching (SCM) in AWS - the angle-delay resolution is adapted to match the size of each SCR. Each angle-delay MF output is now associated with a distinct SCR and consists of the superposition of all sensor transmissions within the SCR. Sec. V discusses incoherent SCM when the different sensors in each SCR can have different relative phases, whereas Sec. VI discusses coherent SCM when the sensors in each SCR transmit in a phase-coherent fashion. Sec. VII discuss the notion of sensing capacity in AWS that could be attained via coded sensor transmissions. As our results indicate, coherent source-channel matching provides a powerful mechanism for dramatically increasing the energy-efficiency and/or capacity of AWS. In all sections, we present numerical results to illustrate the theory. Sec. VIII provides concluding remarks and avenues for future research.
II. THE BASIC SPACE-TIME COMMUNICATION ARCHITECTURE

We first outline the basic assumptions made in this work. Consider an ensemble of $K$ sensors randomly distributed over a region of interest that is interrogated by a wireless information retriever (WIR), as illustrated in Fig. 1(a). We assume that the WIR, equipped with an $M$-element antenna array, is sufficiently far from the sensor ensemble, in the same plane, so that far-field assumptions apply. Furthermore, there exists a strong line of sight path between the WIR and each sensor (no multipath) and the difference in path loss between individual sensors and the WIR can be neglected due to the large distance between the WIR and the sensor field. The WIR interrogates the sensor ensemble by transmitting wideband signaling waveforms, $\{s_m(t)\}$, from different antennas where each $s_m(t)$ is of duration $T$ and (two-sided) bandwidth $W$. Let $N = TW \gg 1$ denote the time-bandwidth product of the signaling waveforms that represents the approximate dimension of the temporal signal space. Thus, the signal space of spatio-temporal interrogation waveforms has dimension $MN = MTW$.

We make the practically feasible assumption that the WIR and the sensor nodes are carrier (frequency) synchronized but not phase synchronized. We assume that the relative phase offset between each sensor and the WIR stays constant at least over two channel uses (roughly over a duration of $2T$, as elaborated later), so that phase estimation is possible. However, in this paper we assume perfect knowledge of relative sensor phases at the WIR; performance with phase estimation is addressed in [9]. Information retrieval at the highest angle-delay resolution constrains the bandwidth to [9]:

$$\frac{c}{\Delta d} < W < \frac{2f_c}{M}$$

where $f_c$ is the carrier frequency, $c$ is the speed of wave propagation, and $\Delta d$ is the minimum distance between the sensors in the direction of the WIR. The lower bound refers to resolution of individual sensors, whereas the upper bound is based on the assumption that the relative time delay between the WIR antennas from any given sensor is negligible compared to the delay resolution $1/W$ (see [9] for details). The above constraints imply that $f_c > \frac{cM}{2\Delta d}$. For example, for a sensor separation of $\Delta d = 1\text{m}$, a WIR with $M = 10$ antennas uses a signaling bandwidth $W \geq 300\text{MHz}$, and a carrier frequency $f_c > 1.5\text{GHz}$.

A. Overview of the Communication Protocol

We now present an overview of the communication protocol in AWS, illustrated in Fig. 2:

- **Frequency synchronization.** The WIR initiates the process by transmitting a carrier signal to synchronize the frequency of sensors’ oscillators.

- **WIR interrogation signal.** The WIR transmits a high power wideband space-time interrogation waveform to a select ensemble of sensors. For simplicity, we assume that the entire ensemble is queried in the interrogation phase.
Sensor waveform acquisition and transmission. The set of sensors which have data to send are termed “active.” In this paper, we assume that all interrogated sensors are active, which is the most challenging scenario. The active sensors encode their data and modulate it onto the temporal signal acquired during the interrogation phase. After a fixed duration (common to all sensors), the sensors transmit their modulated waveforms.

Sensor information extraction at the WIR. The aggregate signal from the active sensors is processed at the WIR to extract the information of interest, such as the individual sensor data or a collective decision statistic.

We note that after the initial interrogation by the WIR, the sensors can continue sending their data using their acquired waveforms. One channel use corresponds to the time taken for sensor transmissions ($T_c = T + \tau_{\text{max}}$) where $\tau_{\text{max}}$ is the maximum relative delay between sensor transmissions. Frequency synchronization as well as estimation of the relative sensor phases (for coherent processing at the WIR) can be done periodically depending on the sensor oscillator characteristics.

B. The Multipath Sensing Channel in AWS

For simplicity, we consider a one-dimensional uniform linear array (ULA) of antennas and assume $M$ to be odd without loss of generality (WLOG), and define $\bar{M} = (M - 1)/2$. The normalized array steering/response vector for a ULA is given by

$$a(\theta) = \sqrt{\frac{1}{\bar{M}}} \left[ e^{j2\pi\bar{M}\theta}, \ldots, 1, \ldots, e^{-j2\pi\bar{M}\theta} \right]^T$$

(1)

where the normalized angle $\theta$ is related to the physical angle of arrival/departure $\varphi$ (see Fig. 1(a)) as $\theta = d \sin(\varphi)/\lambda$. Here $d$ denotes the spacing between the antennas and $\lambda$ is the wavelength of propagation. Due to the relatively large distance from the WIR, we assume that the sensor ensemble projects a limited angular spread at the WIR array: $\varphi \in [-\varphi_{\text{max}}, \varphi_{\text{max}}] \subset [-\pi/2, \pi/2]$ and the antenna spacing is chosen
larger than the critical $\lambda/2$ spacing$^1$, $d = \lambda/2\sin(\varphi_{max})$, so that angular spread of the sensor ensemble is mapped onto the entire $\theta$ range, resulting in a one-to-one mapping between $\theta \in [-0.5, 0.5]$ and $\varphi \in [-\varphi_{max}, \varphi_{max}]$.

The WIR transmits the space-time signal $s(t) = [s_1(t), s_2(t), \ldots, s_M(t)]^T$ in an interrogation packet to initiate information retrieval from the sensor ensemble. The $i$-th sensor acquires a waveform, $x_i(t)$, given by $x_i(t) = e^{-j\phi_i}a^T(\theta_i)s(t - \tau_i)$, where $\theta_i$ denotes the direction of the $i$-th sensor relative to the WIR array (see Fig. 1(a)), $\tau_i$ denotes the relative delay between the $i$-th sensor and the WIR, and $\phi_i \in [0, 2\pi]$ denotes a (random) relative phase between the WIR and the $i$-th sensor. We ignore noise in the acquired waveform $x_i(t)$ since the interrogation signal can be sufficiently strong. The $i$-th sensor encodes its measurement in $\beta_i$, modulates $x_i(t)$ by $\beta_i$, and transmits it with energy $\mathcal{E}$ after a fixed duration following the reception of the interrogation packet. We assume instantaneous retransmission from each sensor for simplicity of exposition. Thus, the transmitted signal from the $i$-th sensor can be expressed as $y_i(t) = \beta_i\sqrt{\mathcal{E}}x_i(t) = \beta_i\sqrt{\mathcal{E}}e^{-j\phi_i}a^T(\theta_i)s(t - \tau_i)$, where $E[|\beta_i|^2] = 1$ and we assume waveform normalization at each sensor, $\int |x_i(t)|^2dt = 1$, so that $y_i(t)$ has energy $\mathcal{E}$. The received vector signal at the WIR, $r(t) = [r_1(t), r_2(t), \ldots, r_M(t)]^T$, is a superposition of all sensor transmissions and, by the principle of reciprocity, it can be expressed as

$$r(t) = \sqrt{\mathcal{E}} \sum_{i=1}^K \beta_i e^{-j\phi_i}a(\theta_i)a^T(\theta_i)s(t - \tilde{\tau}_i) + w(t)$$  \hspace{1cm} (2)$$

where $\tilde{\tau}_i = 2\tau_i$ denotes the round-trip relative delay in the response from the $i$-th sensor, $w(t)$ denotes a vector AWGN process representing the independent noise at different WIR antennas. Assume that $\min_i \tilde{\tau}_i = 0$ and let $\tau_{max} = \max_i \tilde{\tau}_i$ that reflects the delay spread in sensor transmissions. Using (2), the effective system equation relating the received vector signal at the WIR to the transmitted interrogation signal can be expressed as

$$r(t) = \sqrt{\mathcal{E}} \int_0^{\tau_{max}} H(t')s(t - t')dt' + w(t)$$  \hspace{1cm} (3)$$

$$H(t) = \sum_{i=1}^K \alpha_i \delta(t - \tilde{\tau}_i) a(\theta_i)a^T(\theta_i)$$  \hspace{1cm} (4)$$

where $\alpha_i = \beta_i e^{-j\phi_i}$, and the $M \times M$ matrix $H(t)$ represents the impulse response for the *space-time multipath sensing channel* underlying AWS. The delay spread of the channel is $\tau_{max}$ and we assume that the signaling duration $T \gg \tau_{max}$. Thus, each transmission between the sensor ensemble and the WIR is

$^1$We ignore the passive reflections, due to grating lobes, from objects outside the angular spread of the sensor ensemble since the active sensor transmissions will be stronger.
of duration $T_c = T + \tau_{max}$, which defines a single channel use for information retrieval. Sometimes we will refer to a channel use as a transmission packet.

C. Sensor Localization Via Multipath Resolution

The channel matrix (4) in AWS, relating the transmitted and received signal at the WIR, has exactly the same form as the impulse response of a physical multiple-antenna (MIMO) multipath wireless channel where different sensors act as active scatterers and the sensor data and phases $\{\alpha_i = \beta_i e^{-j\phi_i}\}$ correspond to the complex path gains associated with scattering paths in a MIMO multipath channel [18], [19]. In contrast to a MIMO channel, the transmitter and the receiver are co-located (WIR) in AWS. To gain insight into the communication aspects of AWS, we leverage the virtual representation of MIMO multipath channels that is a unitarily equivalent representation of the physical sensing channel matrix [18], [19]. A key property of the virtual channel representation is that its coefficients represent a resolution of sensors in angle and delay commensurate with the signal space parameters $M$ and $W$, respectively.

The virtual representation in angle corresponds to beamforming in $M$ fixed virtual directions: $\tilde{\theta}_m = m/M$, $m = -\tilde{M}, \ldots, \tilde{M}$. Define the $M \times M$ unitary (DFT) matrix, $A = [a(-\tilde{M}/M), \ldots, 1, \ldots, a(\tilde{M}/M)]$, whose columns are the normalized steering vectors for the virtual angles and form an orthonormal basis for the spatial signal space. The virtual spatial matrix $H_V(t)$ is unitarily equivalent to $H(t)$ as

$$H(t) = AH_V(t)A^T \leftrightarrow H_V(t) = A^* H(t) A$$  \hspace{1cm} (5)

and the virtual coefficients, representing the coupling between the $m$-th transmit beam and $m'$-th receive beam are given by

$$H_V(m', m; t) = a^H(m'/M)H(t)a(m/M) = M \sum_{i=1}^{K} \alpha_i g\left(\frac{\theta_i - m'/M}{M}\right) g\left(\frac{\theta_i - m/M}{M}\right) \delta(t - \tilde{\tau}_i) \approx H_V(m, m; t) \delta_{m-m'} \hspace{1cm} (6)$$

$$H_V(m, m; t) \approx M \sum_{i \in S_{\theta,m}} \alpha_i g^2\left(\frac{\theta_i - m/M}{M}\right) \delta(t - \tilde{\tau}_i) \hspace{1cm} (7)$$

where $g(\theta) = \frac{1}{M} \frac{\sin(\pi M \theta)}{\sin(\pi \theta)}$, $g(0) = 1$, is the Dirichlet sinc function that captures the interaction between the fixed virtual beams and true sensor directions, $\delta_m$ denotes the kronecker delta function, and the approximation in (6) is due to the fact that $g(\theta)$ is peaky at the origin and $g(\theta_i - m/M)g(\theta_i - m'/M) \approx \delta_{m-m'}$ [18]. The approximation in (7) follows from virtual path partitioning [18]: $S_{\theta,m} = \{i \in \{1, \ldots, K\} : -1/2M < \theta_i - m/M \leq 1/2M\}$ denotes the set of all sensors whose angles lie in the $m$-th spatial resolution bin of width $\Delta \theta = 1/M$, centered around the $m$-th beam (see Fig. 1(a)). Thus, $H_V(t)$
partitions the sensors in angle: it is approximately diagonal and its $m$-th diagonal entry contains the superposition of all sensor responses that lie within the $m$-th beam of width $1/M$.

The sensor responses within each spatial beam can be further partitioned by resolving their delays with resolution $\Delta \tau = 1/W$. Let $L = \lceil \tau_{max} W \rceil$ denote the normalized delay spread. The diagonal entries of the virtual spatial matrix can be further decomposed into virtual, uniformly spaced delays as

\[
H_V(m, m; t) \approx \sum_{\ell=0}^{L-1} H_V(m, m, \ell) \delta(t - \ell/W)
\]

where $\delta(x)$ is the delta function. The virtual coefficient $H_V(m, m, \ell)$ is a superposition of all sensor responses whose angles and delays lie in the intersection of the $m$-th spatial beam and $\ell$-th delay ring. For a given number of antennas $M$ and a given minimum spacing between sensors $\Delta d$ in the direction of the WIR, the bandwidth $W$ can be chosen sufficiently large, in principle, so that there is exactly one sensor in each angle-delay resolution bin. Specifically, we require $c\Delta \tau = c/W < \Delta d \leftrightarrow W > c/\Delta d$. In this highest-resolution case, we can define one-to-one mappings $i(m, \ell)$ and $(m(i), \ell(i))$ that associate each sensor with a unique angle-delay resolution bin. It follows from (9) that the $(m, \ell)$-th virtual channel coefficient primarily contains the data transmitted by the $i(m, \ell)$-th sensor

\[
h_V(m, \ell) = M \beta_i(m, \ell) \chi_i(m, \ell)
\]

where $\chi_i(m, \ell) = e^{-j\phi_i} g^2(\theta_i - m/M) \text{sinc}(W \tilde{\tau}_i - \ell)|_{i=i(m, \ell)}$.

We note that while the above high-resolution development based on the virtual representation emphasizes the naturally mapping between distinct sensors and distinct angle-delay bins, there will be interference between the sensor responses, in general, as elaborated next.

\[\text{D. Angle-Delay Sufficient Statistics at Highest Resolution}\]

We now describe the basic processing of the received signal $r(t)$ at the WIR for computing the sufficient statistics for information retrieval, as illustrated in Fig. 1(b). We begin by assuming the high resolution case so that each sensor lies in a unique angle-delay resolution bin. Define $s(t) = A^* s_V(t)$ and
\( \mathbf{r}_V(t) = \mathbf{A}^H \mathbf{r}(t) \) where \( \mathbf{s}_V(t) = [s_V(-\tilde{M}; t), \ldots, s_V(\tilde{M}; t)]^T \) and \( \mathbf{r}_V(t) = [r_V(-\tilde{M}; t), \ldots, r_V(\tilde{M}; t)]^T \) are the \( M \)-dimensional transmitted and received signals in the virtual spatial domain (beamspace). In our model, \( \mathbf{s}_V(t) \) represents the temporal codes transmitted by the WIR and acquired by the sensors in different virtual spatial beam directions. Using (3), (5) and (8), the system equation that relates the transmitted and the received signals at the WIR is

\[
\mathbf{r}_V(t) = \sqrt{\frac{\mathcal{E}}{M}} \sum_{\ell=0}^{L-1} \mathbf{H}_V(\ell) \mathbf{s}_V(t - \ell/W) + \mathbf{w}_V(t) \tag{12}
\]

where \( \mathbf{H}_V(\ell) \) represents the virtual spatial matrix (approximately diagonal) corresponding to the \( \ell \)-th virtual delay (see (9)) and \( \mathbf{w}_V(t) \) represents a vector of independent temporal AWGN processes with power spectral density \( \sigma^2 \). Each \( s_V(m; t) \) is a unit-energy pseudo-random waveform with bandwidth \( W \) and duration \( T \) (e.g., a direct-sequence spread spectrum waveform [24]), and we have

\[
\langle s_V(m; t - \ell/W), s_V(m; t - \ell'/W) \rangle \approx \delta_{\ell-\ell'} \tag{13}
\]

Thus, correlating each \( r_V(m; t) \) with delay versions of \( s_V(m; t) \) yields the sufficient statistics for information retrieval \( \{z_{m, \ell} : m = -\tilde{M}, \ldots, \tilde{M} ; \ell = 0, \ldots, L - 1\} \)

\[
z_{m, \ell} = \langle r_V(m; t), s_V(m; t - \ell/W) \rangle = \int_0^{T+\tau_{\text{max}}} r_V(m; t)s_V^*(m; t - \ell/W)dt \tag{14}
\]

While different temporal waveforms can be assigned to different spatial beams in AWS, in the rest of the paper we focus on the attractive special case in which the same unit-energy spread-spectrum waveform, \( c(t) \), is transmitted in all spatial beams; that is, \( s_V(m; t) = c(t) \) for all \( m \). We refer to the \( K \leq ML \) angle-delay resolution bins occupied by distinct transmitting sensors to be active. All further analysis and results presented in this paper assume that all the angle-delay bins are active\(^3\); that is, \( K = ML \). We can express the matched filter (MF) outputs in (14), illustrated in Fig. 1(b), and relate them to the sensor responses as

\[
z_{m, \ell} = \int_0^{T+\tau_{\text{max}}} \mathbf{a}^H(m/M)\mathbf{r}(t)c^*(t - \ell/W)dt = \sqrt{ME} \sum_{i=1}^{K} \beta_i \gamma_i(m, \ell) + w_{m, \ell} \tag{15}
\]

where \( \{w_{m, \ell}\} \) are i.i.d. Gaussian with variance \( \sigma^2 \) and

\[
\gamma_i(m, \ell) = e^{-j\phi_i} g \left( \theta_i - \frac{m}{M} \right) \text{sinc}(W\tau_i - \ell) \tag{16}
\]

\(^2\)The cross-correlation is on the order of \( 1/N = 1/TW \) and thus very small for large \( N \).

\(^3\)When \( K < ML \), the location of active bins/sensors can be reliably determined by the WIR by thresholding the correlator outputs in response to a training interrogation packet. The active sensors respond to a training packet with a sufficiently long string of 1’s to enhance the received SNR at the WIR.
Stacking the MF outputs in a $K = ML$ dimensional vector, we have

$$z = \sqrt{ME} \Gamma \beta + w = \sqrt{ME} \sum_{i=1}^{K} \beta_i \gamma_i + w$$  \hspace{1cm} (17)$$

$$\Gamma = [\gamma_1, \gamma_2, \cdots, \gamma_K]$$  \hspace{1cm} (18)$$

where $\Gamma$ is the $K \times K$ coupling matrix that maps the sensor data vector, $\beta = [\beta_1, \ldots, \beta_K]^T$, to the angle-delay MF output vector $z$. The column vector $\gamma_i$ represents the angle-delay signature generated by the $i$-th sensor at the WIR. The $(m, \ell)$-th component of the $i$-th signature, $\gamma_i(m, \ell)$, in (16) reflects the contribution from the $i$-th sensor to the $(m, \ell)$-th angle-delay bin. Each angle-delay signature is approximately unit-norm, $\|\gamma_i\|^2 = \sum_{m,\ell} |\gamma_i(m, \ell)|^2 \approx 1$, and the factor $\sqrt{M}$ in (17) reflects the array gain.

**Remark 1 (Ideal Case):** When the sensors positions coincide with the center of the resolution bins; that is, $(\theta_i, \tau_i) = (m(i)/M, \ell(i)/W)$ for some $m(i) \in \{-\tilde{M}, \ldots, \tilde{M}\}$ and $\ell(i) \in \{0, \ldots, L-1\}$, $\gamma_i(m, \ell) = e^{-j\phi_i} \delta_{m-m(i)} \delta_{\ell-\ell(i)}$. Consequently, $\gamma_i(m, \ell)$ has a single non-zero value corresponding to the $(m(i), \ell(i))$-th angle-delay bin. It follows that the different sensor angle-delay signatures are orthonormal, $\gamma_i^H \gamma_k = \delta_{i-k}$, and with appropriate re-ordering of sensors, $\Gamma$ is diagonal: $\Gamma = \Phi = \text{diag}(e^{-j\phi_1}, \ldots, e^{-j\phi_K})$ and $\Gamma^H \Gamma = I$, as illustrated in Fig. 3(a). As a result, there is no interference between sensor transmissions – the $(m, \ell)$-th MF output contains only the data transmitted from the corresponding sensor $z_{m,\ell} = \sqrt{ME} \beta_i(m, \ell) e^{-j\phi_i(m, \ell)} + w_{m,\ell}$. □

![Fig. 3. Contour plots of the signature matrix $\Gamma$. (a) Ideal case. (b) Non-ideal case.](image)

In general, when the sensor locations do not coincide with the center of angle-delay bins, $\gamma_i(m, \ell)$ has multiple non-zero components with the largest one in the $(m(i), \ell(i))$-th angle-delay bin and smaller values in other bins. As a result, $\Gamma$ has off-diagonal terms, as illustrated in Fig. 3(b), and there is interference between sensor transmissions. We will address the issue of interference suppression later.
Remark 2 (Distributed MIMO Interpretation): Thus far we have emphasized the roundtrip channel relating the transmitted and received signals at the WIR. The rest of the paper is focused on the channel coupling the sensor ensemble to the WIR as described by (17). This represents a semi-distributed MIMO channel coupling the $K$ distributed sensor transmissions $\beta$ and the $K = ML$ angle-delay MF outputs $z$ at the WIR. The channel is characterized by the signature matrix $\Gamma$ that is diagonally dominant in general and exactly diagonal in the ideal case (see Fig. 3).

III. Canonical Sensing Configurations

We now present a family of canonical sensing configurations in AWS that form the basis of the development in this paper. To start with, we consider uncoded BPSK transmissions from sensors: $\{\beta_i \in \{-1, +1\}\}$. In Sec. VII we discuss the sensing capacity of AWS which may be attained with coded sensor transmissions. The sensor phases $\{\phi_i\}$ are assumed known at the WIR. Phase estimation is possible if the phases are stable for at least two channel uses [9]. In this case, each sensor transmission consists of two packets: a training packet of ‘+1’ for phase estimation followed by a data packet containing the information bit. We note that non-coherent (on-off) signaling is also possible in AWS [9].

![Fig. 4. Canonical sensing configurations at maximum resolution for $K = ML = 9 \times 12 = 108$ active sensors. The sensors are partitioned as $K = K_{\text{ind}}K_{\text{coh}}$ into $K_{\text{ind}}$ groups (SCRs) with $K_{\text{coh}}$ sensors in each SCR. (a) Independent transmissions from all sensors ($K_{\text{ind}} = K = 108$). (b) $K_{\text{ind}} = 9$ SCRs with $K_{\text{coh}} = 12$ sensors transmitting each independent bit.](image-url)
are retrieved in each channel use, whereas $K_{coh}$ sensors in each SCR contribute to transmitting each bit. With the above partitioning, and an appropriate re-ordering of sensors, the $K$-dimensional sensor data vector $\beta$ in (17) can be expressed as

$$\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_K \end{bmatrix} = U \tilde{\beta} = \begin{bmatrix} 1_{K_{coh}} & 0 & \cdots & 0 \\ 0 & 1_{K_{coh}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1_{K_{coh}} \end{bmatrix} \begin{bmatrix} \tilde{\beta}_1 \\ \tilde{\beta}_2 \\ \vdots \\ \tilde{\beta}_{K_{ind}} \end{bmatrix}$$

(19)

where $1_{K_{coh}}$ is a column vector of length $K_{coh}$ containing all ones representing the identical transmissions from the sensors in an SCR. The matrix $U$ is a $K \times K_{ind}$ matrix that maps the $K_{ind}$-dimensional vector, $\tilde{\beta}$, of independent bits to the $K$-dimensional, $\beta$, of sensor transmissions.

The above sensing configurations are an idealized abstraction of correlated sensor measurements: all sensors within each group/SCR have highly correlated measurements, whereas the sensor measurements in different groups are statistically independent, corresponding to independent sensor measurements. This may reflect the intrinsic correlations in the sensor measurements of a homogeneous signal field [13], or may reflect the result of in-network processing where sensors within a group arrive at a consensus statistic reflected in their common bit. The higher the value of $K_{coh}$, the higher the sensor correlation and thus fewer $K_{ind} = K/K_{coh}$ bits capture the information in the sensor ensemble. We note that arbitrary sensing configurations, with non-uniform and non-rectangular SCR’s can also be used. From a distributed MIMO perspective (see Rem. 2), $K_{ind}$ reflects the multiplexing gain – the number of independent parallel (interfering) channels between the sensor ensemble and the WIR – and $K_{coh}$ reflects the number of sensors contributing to each parallel channel.

The next section discusses receiver processing at the WIR for information retrieval at the highest resolution for different canonical configurations (values of $K_{ind}$). Sec. V discusses the case of incoherent source-channel matching in which the angle-delay resolution is matched to the size of the SCRs. Sec. VI discusses the case of coherent source-channel matching in which the sensors in each SCR transmit in a coherent fashion. In each section, we develop the receiver structures for estimating the independent bits, $\tilde{\beta}$, at the WIR and derive expressions for the associated probability of error.

IV. INFORMATION RETRIEVAL AT HIGHEST RESOLUTION

In this section, we describe the signal processing at the WIR for information retrieval in the canonical sensing configurations at the highest resolution: each angle-delay bin corresponds to a distinct sensor. We
consider two receiver structures – with or without interference suppression – and analyze the resulting probability of error, $P_e$, in retrieving the $K_{ind}$ bits of information in each channel use.

Analogous to the sensor re-ordering in (19), we assume WLOG that the first $K_{coh}$ MF outputs correspond to the first group, $S_1$, the second $K_{coh}$ outputs to $S_2$ and so on. Using this re-ordering and (19), the vector of MF outputs can be expressed as

$$z = [z_1^T, z_2^T, \ldots, z_{K_{ind}}^T]^T = \sqrt{M\xi}U\tilde{\beta} + w = \sqrt{M\xi}Q\tilde{\beta} + w = \sqrt{M\xi} \sum_{i=1}^{K_{ind}} \tilde{\beta}_i q_i + w$$  \hspace{1cm} (20)

where the $K_{coh} \times 1$ vector $z_i$ corresponds to the sensors in the $i$-th SCR and

$$Q = \Gamma U = [q_1, q_2, \ldots, q_{K_{ind}}] , \quad q_i = \sum_{k \in S_i} \gamma_k , \quad i = 1, \ldots, K_{ind} .$$  \hspace{1cm} (21)

The $K \times K_{ind}$ matrix $Q$ is the effective signature matrix that couples the $K_{ind}$ independent bits in $\tilde{\beta}$ to the $K$ MF outputs $z$, and $q_i$ is the effective angle-delay signature associated with the bit $\tilde{\beta}_i$ from the $i$-th SCR. Note that $\|q_i\|^2 \approx K_{coh}\|\gamma_i\|^2 = K_{coh}$ reflects the contribution of $K_{coh}$ sensors to each independent bit. We assume perfect knowledge of $Q$ at the WIR. It can be estimated in practice with training sensor transmissions, analogous to phase estimation [9].

**Remark 3 (Ideal Case):** Since $\Gamma = \Phi$ is diagonal (see Rem. 1), (21) implies that $q_i$ has $K_{coh}$ non-zero (phase) values of unit magnitude in the angle-delay bins corresponding to the sensors in the $i$-th SCR, that contribute to the corresponding MF outputs, $z_i$, as illustrated in Fig. 5(a). Thus, the different $q_i$ are orthogonal, $q_i^Hq_k = \sum_{j_1 \in S_i} \sum_{j_2 \in S_k} \gamma_{j_1}^H \gamma_{j_2} = K_{coh}\delta_{i-k}$, $Q^HQ = U^H \Phi^H \Phi U = U^H U = K_{coh}I$, and $\|q_i\|^2 = K_{coh}$. The signature matrix $Q$ in the ideal case is illustrated in Fig. 5(b). \(\square\)
A. Angle-Delay Signature Matched Filtering

In general, the angle-delay signatures, \( \{q_i\} \), are not orthogonal. Due to interference between them, it is well-known that the optimum maximum likelihood (ML) detector of the independent bit vector \( \hat{\beta} \)

\[
\hat{\beta}_{ml} = \arg \max_{\beta \in \{-1,1\}^{K_{ind}}} \|z - \sqrt{M\mathbb{E}}Q\beta\|^2
\]

has exponential complexity in \( K_{ind} \) (see, e.g., [25]). The simplest receiver simply ignores the interference and match filters to the effective angle-delay signatures corresponding to the different SCRs.

\[
\hat{\beta}_{mf} = \text{sign}\{\text{Re}(Q^HZ)\}
\]

The \( i \)-th component of the decision statistic, \( \tilde{z} = Q^HZ \), can be expressed as

\[
\tilde{z}_i = \sqrt{M\mathbb{E}}(q_i^HQ_i)\tilde{\beta}_i + \sqrt{M\mathbb{E}}\sum_{k \neq i}(q_i^HQ_k)\tilde{\beta}_k + q_i^Hw
\]

where \( S_i \) represents the desired signal from the \( i \)-th SCR, \( I_i \) the interference, and \( N_i \) the noise. Using the Gaussian approximation for \( I_i \), the \( P_e \) for the \( i \)-th bit can be characterized as [25]

\[
P_{e,mf}(i) = Q\left( \sqrt{2\text{SINR}_{mf}(i)} \right)
\]

where the Signal-to-Interference-and-Noise-Ratio (SINR) is given by

\[
\text{SINR}_{mf}(i) = \frac{E[|S_i|^2]}{E[|I_i|^2] + E[|N_i|^2]} = \frac{M\mathbb{E}|q_i|^4}{M\mathbb{E}\sum_{k \neq i}|q_i^HQ_k|^2 + |q_i|^2\sigma^2}
\]

Define the per-sensor transmit SNR as

\[
\rho_{sen} = \frac{E}{\sigma^2}.
\]

In general, the MF detector is interference-limited since the \( P_e \) exhibits an error floor in the limit of high \( \rho_{sen} \)

\[
P_{e,mf}(i) \to Q\left( \sqrt{\frac{2||q_i||^4}{\sum_{k \neq i}|q_i^HQ_k|^2}} \right) \text{ as } \rho_{sen} \to \infty.
\]

Under ideal conditions, the interference term in (26) vanishes, and the \( P_e \) reduces to

\[
P_{e,mf,\text{ideal}} = Q\left( \sqrt{2\text{SNR}} \right) = Q\left( \sqrt{\frac{2M\mathbb{E}|q_i|^2}{\sigma^2}} \right) = Q\left( \sqrt{\frac{2M\mathbb{E}K_{coh}}{\sigma^2}} \right) = Q\left( \sqrt{\frac{2M\mathbb{E}K_{coh}}{\sigma^2}} \right)
\]

which is the \( P_e \) for BPSK signaling over an AWGN channel with \( K_{coh} \) times the individual sensor power.

The \( M \)-fold increase in the received SNR at the WIR is due to array gain. The above formula reveals a basic rate-versus-reliability tradeoff in AWS at the highest resolution: increase in rate by increasing \( K_{ind} \) (multiplexing gain) comes at the cost of loss in reliability (SNR) due to a decrease in \( K_{coh} \).
Two extreme cases of this tradeoff are illustrative in the ideal case. On one extreme is the $K_{ind} = 1 \leftrightarrow K_{coh} = K$ case, representing highly redundant/correlated sensing, in which all sensors transmit the same bit; that is, $\beta_i = \tilde{\beta}_1$ for all $i$. The corresponding $P_e$ is given by $P_{e,mf,ideal} = Q \left( \sqrt{\frac{2ME_{\sigma^2}}{\rho_{\text{sen}}}} \right)$. This case represents the low-rate extreme in which a single bit is retrieved in each channel use, although at $K$ times the per-sensor SNR, $\rho_{\text{sen}}$, and hence at high reliability. At the other extreme is the $K_{ind} = K \leftrightarrow K_{coh} = 1$ case representing independent sensing where all sensors transmit independent bits; that is, $\beta_i = \tilde{\beta}_i$ for all $i$. This case represents high-rate information retrieval and a total of $K$ bits are retrieved in each channel use. The $P_e$ is given by $P_{e,mf,ideal} = Q \left( \sqrt{\frac{2ME}{\sigma^2}} \right)$ which is the $P_e$ of BPSK signaling over $K$ parallel AWGN channels each with SNR $\frac{ME}{\sigma^2}$.

B. Linear MMSE Interference Suppression

As noted above, the $P_e$ based on angle-delay signature matched filtering suffers from an error floor. Interference is particularly acute for higher values of $K_{ind}$. Thus, methods for mitigating interference are critical for energy-efficient operation in AWS. The communication channel from the sensor ensemble to the WIR is a multiple access channel (MAC) and the different sensors are analogous to multiple users simultaneously accessing the channel with distinct angle-delay signatures. Thus, a range of multiuser detection techniques [25] can be leveraged. In particular, linear low-complexity interference suppression techniques can yield competitive performance [25]. In this section, we describe a simple linear minimum-mean-squared-error (MMSE) interference suppression technique [25], [26]. The MMSE detector takes the form

$$\hat{\beta}_{\text{mmse}} = \text{sign} \{ \text{Re} (L_{\text{mmse}}z) \}$$  \hspace{1cm} (30)

where the $K_{ind} \times K$ MMSE filter matrix $L_{\text{mmse}}$ is given by

$$L_{\text{mmse}} = \arg \min_L E[\|Lz - \tilde{\beta}\|^2] = Q^H R^{-1}$$  \hspace{1cm} (31)

where $R = E[zz^H] = MEQ^H + \sigma^2 I$ is the correlation matrix of the MF outputs. In (31), $R^{-1}$ suppresses the interference corrupting the MF outputs and the matrix $Q^H$ performs angle-delay signature matched filtering on the resulting filtered MF outputs. The $i$-th filtered decision statistic in $\tilde{z} = L_{\text{mmse}}z$, $\tilde{z}_i$, $i = 1, \ldots, K_{ind}$, can be expressed as

$$\tilde{z}_i = \sqrt{ME} q_i^H R^{-1} q_i \tilde{\beta}_i + \sqrt{ME} \sum_{k \neq i} q_i^H R^{-1} q_k \tilde{\beta}_k + q_i^H R^{-1} w$$  \hspace{1cm} (32)

where $q_i^H R^{-1} q_i$ represents the filtered desired signal and $q_i^H R^{-1} q_k$ the suppressed interference from the $k$-th SCR. Using a Gaussian approximation for the interference [25], the $P_e$ for the $i$-th bit can be
expressed as

\[ P_{e, \text{mmse}}(i) = Q\left( \sqrt{2\text{SINR}_{\text{mmse}}(i)} \right) = Q\left( \frac{2M\mathcal{E}|q_i^H R^{-1} q_i|^2}{\sigma^2||q_i^H R^{-1} q_i||^2 + M\sigma^2 \sum_{k \neq i} |q_i^H R^{-1} q_k|^2} \right) \]  

(33)

We note that the \( P_e \) associated with MMSE filtering does not suffer from error floors [25] as confirmed by the numerical results presented in the next section.

C. Numerical Results

We now illustrate the performance of information retrieval at the highest resolution with numerical results. We consider a WIR equipped with \( M = 9 \) antennas which transmits a single spread-spectrum waveform in all virtual spatial beams: \( s_V(m; t) = c(t) \) for all \( m \), where a length \( N = TW = 127 \) pseudo-random binary code is used for \( c(t) \). We assume that the transmission delays from the sensors to the WIR fall within \( L = 12 \) delay bins, resulting in a total of \( ML = 108 \) angle-delay resolution bins at the highest resolution. We also assume that all the bins are active with a unique sensor associated with each bin: \( K = ML \).

\[ 17 \]

![Figure 6](attachment:image.png)

(a) (b)

Fig. 6. (a) \( P_e \) vs. SNR plots for an AWS system retrieving \( K_{\text{ind}} \) bits per channel use at maximum angle-delay resolution. (b) Comparison of the analytically computed \( P_e \) with numerically estimated values.

The \( P_e \) as a function of the per-sensor transmit SNR, \( \rho_{\text{sen}} \), is shown in Fig. 6(a) for different values of \( K_{\text{ind}} \). The ideal \( P_e \) curves correspond to the ideal case with no interference. All other \( P_e \) (non-ideal) curves correspond to the average performance over multiple random positions of the sensors within their respective bins, and the \( P_e \) reflects the average performance across all active sensors. As \( K_{\text{ind}} \) decreases, the required SNR for a given \( P_e \) is reduced due to an increase in \( K_{\text{coh}} \). Furthermore, the MF detector
incurs a loss in SNR compared to the ideal case and also exhibits a $P_e$ floor due to interference; with increasing $K_{\text{ind}}$, the interference level increases and the $P_e$ saturates at a larger value. On the other hand, the MMSE detector delivers remarkable performance and exhibits no error floors. Fig. 6(b) compares the numerically estimated values of $P_e$ (for the MMSE detector in Fig. 6(a)) with the corresponding analytic expression in (33) based on the Gaussian approximation. As evident, the agreement is quite good.

V. INCOHERENT SOURCE-CHANNEL MATCHING

![Diagram](a)

![Diagram](b)

![Diagram](c)

![Diagram](d)

Fig. 7. Illustration of incoherent source-channel matching (ISCM). (a) Active bins at the WIR at the highest resolution corresponding to a canonical sensing configuration with $K_{\text{ind}} = 12$ and $K = 108$. (b) $K_{\text{ind}} = 12$ active angle-delay resolution bins at the WIR corresponding to ISCM via reduced angle-delay resolution; $K_{\text{coh}}$ sensors incoherently contribute to each angle-delay bin. (c) The $K_{\text{coh}}$ sensor transmissions in each SCR are mapped to a single MF output, in effect creating a $K_{\text{coh}} \times 1$ incoherent MAC between each SCR and the WIR. (d) Contour plot of the ideal signature matrix $D$ for $K_{\text{ind}} = 12$.

In information retrieval at the highest resolution, each angle-delay resolution bin is associated with a distinct sensor. In effect, $K$ parallel (interfering) channels are created between the $K$ sensors and the WIR via angle-delay matched filtering. However, in the canonical sensing configurations, the $K_{\text{coh}}$ sensors in each SCR transmit the same bit and thus do not need to be individually resolved. In this section, we
consider the case of incoherent source-channel matching (ISCM) in which the angle-delay resolution is matched to the size of the SCR’s. As illustrated in Fig. 7(a) and (b), in ISCM the angle-delay resolution is reduced so that each angle-delay bin corresponds to a distinct SCR rather than a distinct sensor in the high-resolution case. In effect, the $K_{coh}$ parallel channels between each SCR and the WIR at the highest resolution are transformed into an incoherent $K_{coh} \times 1$ MAC, since the sensor phases in each SCR can be different. Thus, there are $K_{ind}$ distinct angle-delay resolution bins at the WIR (as opposed to $K$ bins at the highest resolution) and the $K_{coh}$ sensor transmissions from each SCR incoherently contribute to the corresponding angle-delay bin, as illustrated in Fig. 7(c) (Compare with Fig. 5(a.).)

The idea of reduced angle-delay resolution to realize ISCM is illustrated in Fig. 7 for $K = 108$, $K_{ind} = 9$ and $K_{coh} = 12$. Let $K_{ind} = M_{ind}L_{ind} \mapsto K_{coh} = M_{coh}L_{coh}$ so that each SCR with $K_{coh} = 12$ sensors corresponds to $L_{coh} = 4$ delay bins and $M_{coh} = 3$ angle bins at the maximum resolution, as illustrated in Fig. 7(a). ISCM involves two key effects in each SCR, as illustrated in Fig. 7(b): i) the angular resolution is reduced by a factor $M_{coh}$ so that the $M_{coh}$ angle bins in Fig. 7(a) get mapped to a single bin in Fig. 7(b); ii) the delay resolution is reduced by a factor of $L_{coh}$ so that the sensor transmissions in distinct $L_{coh}$ delay bins at the highest resolution in Fig. 7(a) are mapped to a single delay bin in Fig. 7(b). Alternatively, ISCM may also arise when the sensors are densely spaced compared to the angle-delay resolution so that multiple sensor transmissions contribute to each angle-delay bin.

The effective system equation for ISCM can be inferred from the system equation (20) at maximum resolution as

$$z_{isc} = [z_{isc,1}, z_{isc,2}, \ldots, z_{isc,K_{ind}}]^T = \sqrt{M\varepsilon} U^H \Gamma U \tilde{\beta} + \mathbf{w}_{isc} = \sqrt{M\varepsilon} \sum_{i=1}^{K_{ind}} \tilde{\beta}_i d_i + \mathbf{w}_{isc} \quad (34)$$

where the the $K_{ind} \times K_{ind}$ signature matrix

$$D = U^H \Gamma U = U^H Q = [d_1, \cdots, d_{K_{ind}}] = [U^H q_1, \cdots, U^H q_{K_{ind}}] \quad (35)$$

represents the coupling between the $K_{ind}$ independent sensor transmissions and the $K_{ind}$ active angle-delay resolution bins at the WIR, and the $K_{ind} \times 1$ vectors, $d_i$, represent the effective angle-delay signatures associated with the $i$-th transmitted bit $\tilde{\beta}_i$ from the $i$-th SCR.

The receivers at the WIR for ISCM can be designed using the system equation (34), parallel to the high-resolution case. The MF detector is given by $\hat{\tilde{\beta}}_{mf} = \text{sign} \{ \text{Re} (D^H z_{isc}) \}$ and the $P_{e,isc,mf}(i) = Q(\sqrt{2\text{SINR}_{mf}(i)})$ associated with the $i$-th bit can be estimated using the expression for $\text{SINR}_{mf}(i)$ in (26) by replacing $\{q_i\}$ with $\{d_i\}$. Similarly, the MMSE detector is given by $\hat{\tilde{\beta}}_{mmse} = \text{sign} \{ \text{Re} (L_{isc,mmse} z_{isc}) \}$.
where the $K_{\text{ind}} \times K_{\text{ind}}$ filter matrix $L_{\text{isc,mmse}}$ is given by

$$L_{\text{isc,mmse}} = \arg\min_L E[\|Lz_{\text{isc}} - \hat{\beta}\|_2^2] = D^H R_{\text{isc}}^{-1}$$  \hspace{1cm} (36)$$

and $R_{\text{isc}} = E[z_{\text{isc}}z_{\text{isc}}^H] = MEDD^H + \sigma^2 I$ is the correlation matrix of the matched filter outputs. The $P_e$ of the MMSE receiver, $P_{e,\text{isc,mmse}}(i)$ can be approximated similar to (33) as

$$P_{e,\text{isc,mmse}}(i) = Q\left(\frac{2ME|d_i^H R_{\text{isc}}^{-1}d_i|^2}{\sigma^2|d_i^H R_{\text{isc}}^{-1}d_i|^2 + ME \sum_{k \neq i} |d_i^H R_{\text{isc}}^{-1}d_k|^2}\right).$$  \hspace{1cm} (37)$$

The performance of ISCM is dictated by two competing phenomena. On the one hand, reducing the number of MF outputs to match $K_{\text{ind}}$ reduces the noise contribution to each MF output. On the other hand, since $K_{\text{coh}}$ incoherent sensor transmissions contribute to each MF output (angle-delay bin), the resulting signal may be weaker or stronger depending on the instantaneous phases. As elaborated next for the ideal case, this effectively results in a fading channel connecting each SCR to the WIR. In particular, the above expressions for $P_e$ are conditioned on a given realization of the sensor phases in each SCR and hence on a particular realization of the signature vectors $\{d_i\}$.

**Remark 4 (Ideal Case):** Since $\Gamma = \Phi$ is diagonal (see Rem. 1), from (35) we have $D = U^H Q = U^H \Phi U$. The $K \times 1$ high-resolution signature $q_i$ consists of $K_{\text{coh}}$ phase terms in the coordinates corresponding to the $i$-th SCR (see Rem. 3). Hence, the $K_{\text{ind}} \times 1$ signature $d_i = U^H q_i$ in ISCM consists of all zeros except a single non-zero entry which is the sum of $K_{\text{coh}}$ independent phases in the coordinate corresponding to the $i$-th SCR, that is $d_i(n) = \sum_{k \in S_i} e^{-j\phi_k} \delta_{n-i}$. The magnitude of this non-zero entry depends on the instantaneous phases of the $K_{\text{coh}}$ sensor transmissions in the SCR and as a result $||d_i||^2$ is a random quantity with $E[||d_i||^2] = K_{\text{coh}}$. However, the different signatures are still orthogonal: $D^H D = \text{diag}(||d_1||^2, \ldots, ||d_{K_{\text{ind}}}||^2)$. The signature matrix $D$ in the ideal case is illustrated in Fig. 7(d). □

The $P_e$ and SNR expressions in the ideal case are useful to infer the effect of incoherent sensor transmissions in each SCR in ISCM relative to information retrieval at the highest resolution. The $i$-th matched filter output is

$$z_i = \sqrt{ME} \hat{\beta}_i \sum_{k \in S_i} e^{-j\phi_k} + w_i$$  \hspace{1cm} (38)$$

and the $\sum_{k \in S_i} e^{-j\phi_k}$ term effectively introduces fading (as values of $\{\phi_k\}$ vary) that results in fluctuations in the instantaneous received SNR at the WIR. The average received SNR

$$E[\text{SNR}(i)] = \frac{ME\mathbb{E}\left[\sum_{k \in S_i} e^{-j\phi_k}\right]}{\sigma^2} = \frac{MEK_{\text{coh}}}{\sigma^2}$$  \hspace{1cm} (39)$$
is the same as that in the highest resolution case. However, since the instantaneous SNR can fluctuate above and below the average, the long-term average probability of error, including averaging over the sensor phases, is given by: 

$$P_{e,isc,ideal} = E \left[ Q \left( \sqrt{2SNR(i)} \right) \right].$$

Modeling $|\sum_{k \in S_i} e^{-j\phi_i}|$ as a Rayleigh random variable (if $K_{coh}$ is sufficiently large), the probability of error can be approximated as [24]

$$P_{e,isc,ideal} \approx \frac{1}{2} \left( 1 - \sqrt{\frac{E[SNR(i)]}{1 + E[SNR(i)]}} \right) \approx \frac{1}{4E[SNR(i)]} = \frac{1}{4\rho_{sen}MK_{coh}}$$

(40)

where $\rho_{sen} = \mathcal{E}/\sigma^2$ is the per-sensor transmit SNR. Thus, the performance in ISCM suffers considerably due to the phase incoherence in the sensors’ transmissions in each SCR, as illustrated by the numerical results in the next section. Note that the same averaging over sensor phases should be done in earlier expressions for $P_e$ in the general case to compute long-term average $P_e$.

A. Numerical Results

We present numerical results to illustrate the performance of AWS in an ISCM configuration. The simulation set up is identical to the one in Sec. IV-C. The probability of error $P_e$ as a function $\rho_{sen} = \mathcal{E}/\sigma^2$ is shown in Fig. 8(a), along with the corresponding plots for the high-resolution case. The $P_e$ for the MMSE detector in ISCM is computed by averaging the expression in (37) over multiple independent phases for the sensors. The scaling behavior of $P_e$ with $\rho_{sen}$ due to fading (see (40) for the ideal case) and the resulting loss in SNR compared to the high-resolution case is evident. Fig. 8(b) compares the numerically estimated values of $P_e$ (for the MMSE detector) with the corresponding averaged value (over phase realizations) of the analytic expression in (37).

![Fig. 8. (a) $P_e$ vs. SNR plots for an AWS system in an ISCM configuration relative to those for high-resolution sensing. (b) Comparison of the analytically computed $P_e$ values with numerically estimated values for the non-ideal scenario with MMSE filtering.](image-url)
VI. COHERENT SOURCE-CHANNEL MATCHING

Fig. 9. Illustration of coherent source-channel matching (CSCM). (a) Active angle-delay resolution bins at the WIR corresponding to a canonical sensing configuration, $K = 108$, $K_{\text{ind}} = 12$, at the highest resolution. (b) Active angle-delay resolution bins at the WIR corresponding to CSCM; only $K_{\text{ind}}$ angle-delay bins are active at the WIR and $K_{\text{coh}}$ sensor transmissions from each group contribute coherently to each bin. (c) The $K_{\text{coh}}$ sensor transmissions in each SCR are coherently mapped to a single MF output at the WIR. (d) A contour plot of the ideal signature matrix $V$.

In maximum resolution sensing, each sensor transmission is associated with a distinct angle-delay bin or MF output, whereas in the canonical sensing configurations, only $K_{\text{ind}} \leq K$ independent bits are transmitted and $K_{\text{coh}} = K/K_{\text{ind}}$ sensors in each group transmit the same bit (see Fig. 5(a)). These identical transmissions are coherently combined at the receiver after matched filtering to the $K$-dimensional angle-delay signatures $q_i$, $i = 1, \ldots, K_{\text{ind}}$. However, in the process, all $K$ MF outputs, along with their individual noises, contribute to the decoding of the independent bit from each SCR. In the ISCM scenario, we reduce the number of noise sources to $K_{\text{ind}}$ by converting the $K_{\text{coh}}$ parallel channels between the sensors in each SCR and the WIR into a $K_{\text{coh}} \times 1$ MAC (see Fig. 7(c)). However, due to the phase incoherence in the sensors’ transmitted signals, we take a significant loss in SNR in long-term $P_e$ performance, due to essentially a form of fading. Coherent source-channel matching (CSCM) builds
on the ISCM configuration with reduced angle-delay resolution, as illustrated in Fig. 9. The motivation for CSCM is to coordinate the phases of the transmissions from the $K_{coh}$ sensors in each SCR so that, in effect, they are *coherently* combined during communication over the channel and the combined signal gets mapped to a single angle-delay bin at the WIR, as illustrated in Fig. 9(a)-(b). Thus, CSCM converts the $K_{coh} \times 1$ *incoherent* MAC connecting each SCR to the WIR in the ISCM case to a $K_{coh} \times 1$ *coherent* MAC, as illustrated in Fig. 9(c). This is achieved through a form of distributed *angle-delay focussing*: the $K$ sensor transmissions are now naturally mapped to $K_{ind}$ distinct active angle-delay bins at the WIR (as in the ISCM), and $K_{coh}$ sensor transmissions from SCR *coherently* contribute to each active MF output. 

Recall the factoring $K_{ind} = L_{ind} M_{ind} \leftrightarrow K_{coh} = L_{coh} M_{coh}$, as in the ISCM case. CSCM involves three key effects in each SCR: i) the angular resolution is reduced by a factor $M_{coh}$ so that the $M_{coh}$ angle bins in Fig. 9(a) get mapped to a single angle bin in Fig. 9(b); ii) the sensor transmissions in distinct $L_{coh}$ delay bins in Fig. 9(a) are “lined-up” in time so that they lie in a single delay bin as in Fig. 9(b); and iii) the $K_{coh}$ sensors in each group that now lie in a single angle-delay bin in Fig. 9(b) transmit in a *phase-coherent* fashion, as illustrated in Fig. 9(c). ISCM and CSCM differ in the third crucial step. As in ISCM, the second step could also be realized by reducing the delay resolution by a factor $L_{coh}$, as in Fig. 7(b), as opposed to temporally lining up the sensor transmissions at high resolution as in Fig. 9(b). 

The effective system equation for CSCM can be expressed using (20) as 

$$
\begin{align*}
\mathbf{z}_{\text{esc}} &= [z_{\text{esc},1}, z_{\text{esc},2}, \ldots, z_{\text{esc},K_{ind}}]^T = \sqrt{ME} Q^H Q \tilde{\beta} + \mathbf{w}_{\text{esc}} = \sqrt{ME} \sum_{i=1}^{K_{ind}} \tilde{\beta}_i \mathbf{v}_i + \mathbf{w}_{\text{esc}}
\end{align*}
$$

(41)

where the $K_{ind} \times K_{ind}$ signature matrix 

$$
V = Q^H Q = [v_1, \ldots, v_{K_{ind}}] = [Q^H q_1, \ldots, Q^H q_{K_{ind}}]
$$

(42)

represents the coherent coupling between the $K_{ind}$ independent bits and the $K_{ind}$ active angle-delay bins at the WIR, and the $K_{ind} \times 1$ vectors, $\{\mathbf{v}_i\}$, represent the effective *angle-delay focussed* signatures associated with the $i$-th transmitted bit $\tilde{\beta}_i$. Due to the coherent angle-delay focussing, we have the following relation between $\mathbf{v}_i$, $\mathbf{q}_i$ and $\gamma_i$ 

$$
||\mathbf{v}_i||^2 \approx K_{coh} ||\mathbf{q}_i||^2 \approx K_{coh}^2 ||\gamma_i||^2 = K_{coh}^2,
$$

(43)

where the approximations are exact in the ideal case. Recall that the signature vectors in ISCM are random (due to incoherent sensor transmissions) and satisfy $E[||\mathbf{d}_i||^2] = ||\mathbf{q}_i||^2 = K_{coh}$.

As in the previous cases, the receivers for CSCM can be designed using the system equation (41). The signature matched filter receiver is given by 

$$
\hat{\beta}_{mf} = \text{sign}\{\text{Re}(V^H \mathbf{z}_{\text{esc}})\}
$$

and the $P_{e,\text{esc},mf}(i) =$
$Q\left(\sqrt{2\text{SINR}_{\text{mf}}(i)}\right)$ associated with the $i$-th bit can be computed by using the expression for $\text{SINR}_{\text{mf}}(i)$ in (26) by replacing $\{q_i\}$ with $\{v_i\}$. Similarly, the MMSE receiver is given by $\hat{\beta}_{\text{mmse}} = \text{sign}\{\text{Re}\left(L_{\text{csc,mmse}}z_{\text{csc}}\right)\}$ where the $K_{\text{ind}} \times K_{\text{ind}}$ matrix $L_{\text{csc,mmse}}$ is given by

$$L_{\text{csc,mmse}} = V^H R_{\text{csc}}^{-1}$$

(44)

and $R_{\text{csc}} = E[z_{\text{csc}}z_{\text{csc}}^H] = MEV^H + \sigma^2 I$. The corresponding probability of error, $P_{e,\text{csc,mmse}}$, can be computed using (37) by replacing $\{d_i\}$ with $\{v_i\}$ and $R_{\text{isc}}$ with $R_{\text{csc}}$.

Remark 5 (Ideal Case): Since $\Gamma = \Phi$ is diagonal (see Rem. 1), $Q = \Phi U$ and from (42) we have $V = U^H \Phi^H \Phi U = K_{\text{coh}} I$. In the high resolution case, the $K \times 1$ signature $q_i$ consists of all zeros except $K_{\text{coh}}$ unit magnitude (phase) entries in the coordinates corresponding to the $i$-th SCR. On the other hand, the “focussed” $K_{\text{ind}} \times 1$ signature $v_i$ consists of all zeros except a non-zero entry of size $K_{\text{coh}}$ in the coordinate corresponding to the $i$-th SCR. The increase in magnitude of the non-zero entry is due to the phase-coherent transmissions from $K_{\text{coh}}$ sensors in the SCR (see Fig. 9(c)). Thus, the signature vectors are orthogonal, $V^H V = K_{\text{coh}}^2 I$, and the energy coupled to the WIR from each SCR, $\|v_i\|^2 = K_{\text{coh}}^2 \|q_i\|^2 = K_{\text{coh}}^2$, is a factor of $K_{\text{coh}}$ higher than that at the highest resolution. In relation to the ISCM configuration, CSCM corresponds to aligning the phases of sensors in each SCR so that they contribute coherently to the corresponding MF output, resulting in the highest SNR at the receiver.

The $P_e$ in the ideal case is useful in comparing the performance of the CSCM relative to information retrieval at the highest resolution and ISCM:

$$P_{e,\text{csc,ideal}} = Q\left(\sqrt{\frac{2ME\|v_i\|^2}{\sigma^2}}\right) = Q\left(\sqrt{\frac{2ME}{\sigma^2} \left(\frac{K}{K_{\text{ind}}}\right)^2}\right) = Q\left(\sqrt{\frac{2MEK_{\text{coh}}^2}{\sigma^2}}\right).$$

(45)

Comparing the above expression with (29) we note that coherent source-channel matching affords an SNR gain of $K_{\text{coh}}$ compared to information retrieval at the highest resolution and does not suffer the loss in performance due to fading in ISCM (see (40)).

A. Numerical Results

We now present numerical results to illustrate the performance of information retrieval with CSCM. The simulation set up is the same as in Sec. IV-C. The $P_e$ as a function of the per-sensor transmit SNR, $\rho_{\text{sen}}$, is shown in Fig. 10(a). Note that although the $P_e$ behavior as a function of $K_{\text{ind}}$ is similar to that of the maximum resolution case, the SNR required to attain a desired $P_e$ is substantially reduced due to the $K_{\text{coh}}$ SNR gain. For the matched filter receiver, there is a loss in SNR in the non-ideal case and also a $P_e$ floor due to interference, as expected. However the performance is near-ideal for the MMSE receiver.
Note that the phase-coherent sensor transmissions eliminate the detrimental phenomenon of fading which dominated the $P_e$ behavior in the case of ISCM. Coherent source-channel matching effectively corresponds to an ISCM system with the highest instantaneous SINR (coherent sensor phases). Fig. 10(b) compares the performance gains due to coherent SCM relative to information retrieval at the highest resolution. Even in the non-ideal case, CSCM provides an SNR gain of approximately $10 \log(K_{coh})$ dB compared to information retrieval at the maximum resolution. For example, when $K_{ind} = 6 \Rightarrow K_{coh} = 18$, the $P_e$ curves are spaced by about 12dB. For a constant $K'$, decreasing $K_{ind}$ increases $K_{coh}$ and hence the gain due to CSCM is even more pronounced for smaller values of $K_{ind}$.

### B. Realizing the Source-Channel Matched Architecture

How do we adapt the angle-delay resolution in source-channel matching, illustrated in Figs. 7 and 9? The reduction in angular resolution can be achieved by reducing the antenna spacings at the WIR by a factor of $M_{coh}$ ($M_{coh} = 3$ in Fig. 9) [20], [21]. This effectively results in $M/M_{coh} = M_{ind}$ distinct spatial beams, each with a $M_{coh}$ times wider beamwidth [20], [21]. Alternatively, the carrier frequency could be reduced by a factor $M_{coh}$ to attain the same effect. Distributed time-reversal techniques [27] can be used to line up the sensor transmissions in $L_{coh}$ ($L_{coh} = 4$ in the figure) distinct delay bins into a single delay bin, as illustrated in Fig. 9(b). Alternatively, the delay resolution could be reduced by a factor $L_{coh}$ by decreasing the signaling bandwidth by a factor $L_{coh}$, as in Fig. 7(b). The above two steps reduce the angle-delay resolution, so that it is matched to the size of the SCRs in the sensing configuration. Finally, distributed beamforming algorithms [28] could be applied in each SCR to make the $K_{coh}$ sensor transmissions, that correspond to a single angle-delay bin in Fig. 7(b) or Fig. 9(b), phase coherent.
VII. Sensing Capacity

Thus far we have analyzed the performance of AWS for uncoded coherent BPSK transmissions from the sensors. In this section, we discuss the notion of sensing capacity in AWS – the highest rate of information retrieval – that may be attained via coded transmissions from the sensors. Furthermore, we address the following question: how does the sensing capacity vary for different sensing configurations as a function of $K_{ind}$ and the per-sensor transmit SNR ($\rho_{sen}$)? As we will see, the answer in the case of coherent source-channel matching is surprising and reflects the SNR gain proportional to $K^2_{coh}$.

As mentioned earlier, AWS effectively creates a semi-distributed MIMO channel between the $K$ sensors and the WIR via angle-delay matched filtering. The capacity for any given sensing configuration is governed by the underlying matrix, $H$, that couples the $K_{ind}$ SCRs and the WIR: $H = Q, D, V$ in the case of high-resolution sensing, incoherent source-channel matching and coherence source-channel matching, respectively. Using results on the capacity of MIMO channels [29], the sensing capacity of AWS can be computed as

$$C(K_{ind}) = \frac{1}{TW + L} \log_2 \left| I + \frac{EM}{\sigma^2} HH^H \right|$$

$$\approx \frac{1}{TW + L} \sum_{i=1}^{K_{ind}} \log_2 (1 + \text{SINR}(i)) \text{ b/s/Hz}$$

(46)

(47)

where (46) reflects the mutual information of a MIMO channel characterized by $H = \{Q, D, V\}$ under the assumption of equal power and independent transmissions from the different SCR’s, and the factor $TW + L$ is the signaling time-bandwidth product for each channel use. The approximation in (47) reflects the sum capacity of the $K_{ind}$ parallel channels between the sensor ensemble and the WIR and can be used for estimating capacity with the matched filter or the MMSE receiver by plugging in the appropriate expression for SINR$(i)$.

To study the impact of sensing configuration and coherent source-channel matching, we focus on the ideal case to get insight so that $\text{SINR} \rightarrow \text{SNR}$ and it is the same for all parallel channels. As our numerical results indicate, the analysis in the ideal case accurately reflects the capacity in the non-ideal case. Furthermore, the capacity expression in the ideal case is exact and corresponds to the capacity of $K_{ind}$ parallel AWGN channels, each operating at the same SNR. We primarily consider two cases: maximum resolution, $H = Q$, and coherent source-channel matching, $H = V$. In the maximum resolution case, (47) simplifies to

$$C_{ideal}(K_{ind}) = \frac{K_{ind}}{TW + L} \log_2 \left( 1 + \frac{EM}{\sigma^2} \frac{K}{K_{ind}} \right)$$

(48)
whereas in the case of coherent source-channel matching we have

$$C_{\text{ideal,csc}}(K_{\text{ind}}) = \frac{K_{\text{ind}}}{TW + L} \log_2 \left( 1 + \frac{ME}{\sigma^2} \left( \frac{K}{K_{\text{ind}}} \right)^2 \right)$$  \hspace{1cm} (49)$$

which reflects an SNR gain of $K_{\text{coh}}$ per parallel channel compared to the maximum resolution case.

![Graphs](a)(b)(c)

Fig. 11. Sensing capacity of AWS with the MMSE receiver (non-ideal case) as a function of $\rho_{\text{sen}}$ for different values of $K_{\text{ind}}$. (a) Information retrieval at maximum resolution. (b) Information retrieval with coherent source-channel matching (c) Comparison of the capacity, plotted on a linear scale, in the ideal case with that in the non-ideal case with CSCM.

From (48) we note that the sensing capacity is a monotonic function of $K_{\text{ind}}$ in the maximum resolution case. This is illustrated in Fig. 11(a) where the capacity for the non-ideal case with the MMSE receiver (using (47)) is plotted as a function of per-sensor transmit SNR, $\rho_{\text{sen}}$, for different values of $K_{\text{ind}}$. As evident, at high SNRs, the capacity is maximum for $K_{\text{ind}} = K$ and minimum for $K_{\text{ind}} = 1$. On the other hand, this increase in capacity with $K_{\text{ind}}$ diminishes at low SNRs and the curves for the two extremes coincide.
Fig. 11(b) plots the non-ideal sensing capacity as a function of \( \rho_{\text{sen}} \) for CSCM for different values of \( K_{\text{ind}} \). In this case, the capacity is not a monotonic function of \( \rho_{\text{sen}} \). At high SNRs, the \( K_{\text{ind}} = K \) configuration yields the highest capacity, as in the high resolution case, whereas \( K_{\text{ind}} = 1 \) yields the lowest capacity. However, at low SNRs, the roles are reversed: the \( K_{\text{ind}} = 1 \) configuration yields the highest capacity and \( K_{\text{ind}} = K \) yields the lowest capacity. Most importantly, at every \( \rho_{\text{sen}} \) there is an optimum sensing configuration, \( K_{\text{ind}, \text{opt}}(\rho_{\text{sen}}) \), that yields the highest capacity. In particular, the configuration \( K_{\text{ind}} = \sqrt{K} \) is a robust choice whose capacity remains between the extreme cases of \( K_{\text{ind}} = K \) and \( K_{\text{ind}} = 1 \). In fact, the expression for \( C_{\text{csc,ideal}} \) reveals a fundamental multiplexing gain versus received SNR tradeoff that we have also recently discovered in the context of MIMO communication over sparse multipath channels [20], [21]: increasing the multiplexing gain (\( K_{\text{ind}} \)) comes at the cost of decreasing the received SNR per parallel channel, \( \rho_{\text{rx}} = \rho_{\text{sen}} M (K/K_{\text{ind}})^2 \), and vice versa. The optimal configuration at any \( \rho_{\text{sen}} \) optimizes this tradeoff to yield the highest capacity. Using the results of [20], [21], we can characterize the optimal configuration in the ideal case, for any operating \( \rho_{\text{sen}} \), as

\[
K_{\text{ind}, \text{opt,csc}}(\rho_{\text{sen}}) \approx \left\{ \begin{array}{ll}
1, & \rho_{\text{sen}} \leq \rho_{\text{low}} = \frac{4}{MK^2} \\
\sqrt{\frac{M\rho_{\text{sen}}}{2}}, & \rho_{\text{sen}} \in (\rho_{\text{low}}, \rho_{\text{high}}) \\
K, & \rho_{\text{sen}} \geq \rho_{\text{high}} = \frac{4}{M}
\end{array} \right.
\]

Fig. 11(b) also shows the capacity of an equivalent AWGN channel with the total receive SNR \( \rho_{\text{total}} = \rho_{\text{sen}} M K \) reflecting the situation in which a single sensor (a fusion node) transmits the data (in the \( K_{\text{ind}} \) symbol streams) using the total power used by the entire ensemble of \( K \) nodes. As evident, optimized coherent source-channel matching affords the maximum multiplexing gain over the AWGN capacity over the entire SNR range, reflecting the \( K \)-fold distributed MIMO capacity gain. Fig. 11(c) compares the capacity in the ideal and non-ideal cases for CSCM on a linear scale to emphasize any loss due to interference. The deviation between ideal and non-ideal cases is relatively small and increases with larger \( K_{\text{ind}} \) due to higher interference.

VIII. CONCLUSIONS

Active Wireless Sensing (AWS) exploits the advanced functionality afforded by wideband, agile RF front-ends and reconfigurable antenna arrays for rapid and energy-efficient information retrieval in sensor networks. The key underlying idea is to distinguish individual sensor responses by exploiting the differences in the space-time (angle-delay) signatures generated by them. Our analysis based on the canonical sensing configurations and source-channel matching shows that adapting the spatio-temporal resolution in AWS to the spatial correlation in the signal field (or the spatial scale of cooperation in the network) can
greatly enhance energy efficiency. In particular, coherence source-channel matching yields the highest gains both in terms of energy efficiency and rate of information retrieval.

There are many exciting avenues for future work. First, while the focus of this paper was on line-of-sight (LOS) communication, in practice the sensing channel will likely involve multipath scattering between the sensor ensemble and the WIR. Our initial results in this challenging scenario indicate that multipath, in addition to LOS, can further enhance energy efficiency [30]. On the other hand, sensor localization information that is readily available in the LOS scenario is compromised. However, time-reversal techniques could be leveraged for sensor localization in the presence of multipath. Second, a comprehensive energy comparison between in-network processing and AWS, that takes into account the related overheads (routing in in-network processing, and establishing node cooperation in AWS), also warrants further investigation. Third, while we assumed perfect knowledge of the signature matrices \((\Gamma, Q, D, V)\) in this paper, they will need to be estimated in practice. Thus, analysis of the impact of estimation errors on the performance of AWS would be useful for practical implementation. In this regard, developing non-coherent communication protocols in AWS is also an interesting direction. Finally, extending recent work on data-driven modulation (see, e.g., [14], [15], [31], [32]) in the context of AWS would also be fruitful.

REFERENCES


