ACTIVE WIRELESS SENSING: SPACE-TIME INFORMATION RETRIEVAL FROM SENSOR ENSEMBLES

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ABSTRACT

Existing approaches for information extraction in wireless sensor networks are heavily geared towards in-network processing, which generally incurs excess delay and energy consumption due to the attendant tasks of information routing and coordination between nodes. In this paper, we introduce an alternative concept of Active Wireless Sensing in which a wireless information retriever (WIR) interrogates a select ensemble of nodes for rapid and energy-efficient retrieval of desired information. Active Wireless Sensing has two primary attributes: i) the sensor nodes are "dumb" in that they have limited computational ability, and ii) the WIR is computationally powerful, is equipped with an antenna array, and directly interrogates the sensor ensemble with wideband space-time waveforms. Our approach is based on an intimate connection between Active Wireless Sensing and wideband multi-antenna wireless channels in multipath propagation environments: the sensor nodes play the role of active scatterers and generate a multipath response to WIR's interrogation signals. We illustrate the basic communication architecture in Active Wireless Sensing and the corresponding signal processing at the WIR. Preliminary simulation results are presented to illustrate a fundamental rate versus reliability tradeoff in Active Wireless Sensing.

1. INTRODUCTION

Existing approaches to information extraction in a wireless sensor network are heavily geared towards in-network processing where either the network as a whole obtains a consistent estimate of desired information (e.g., field data, or some summary statistic), or the distributed information is routed to a decision center via multi-hop routing [1]. However, in-network processing generally incurs excess delay and energy consumption due to the attendant tasks of information routing and coordination between nodes (e.g., in-network iterative algorithms). In this paper we propose an alternative approach – Active Wireless Sensing — in which a wireless information retriever (WIR) interrogates a select ensemble of sensor nodes for rapid and energy-efficient retrieval of desired information (see Fig. 1). Active Wireless Sensing has two primary attributes: i) the sensor nodes are relatively "dumb" in that they have limited computational power, and ii) the WIR is computationally powerful, is equipped with a multi-antenna array, and initiates the information retrieval by interrogating the nodes with wideband space-time waveforms.

Active Wireless Sensing is similar, in terms of the underlying physics, to the concept of Imaging Sensor Nets that has been independently proposed recently [2, 3] based on radar imaging principles. In contrast, our approach is based on an intimate connection between Active Wireless Sensing and 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 signals. A key idea behind Active Wireless Sensing is to separate different sensor responses by resolving the multipath signals in angle and delay. This is facilitated by a virtual representation of wideband space-time wireless channels that we have developed in the past several years [4, 5]. Our proposal for Active Wireless Sensing with an emphasis on distributed communication protocols in conjunction with the Imaging approach of [2, 3] also provides a connection between radar imaging and wireless communication over multipath channels. We believe that these two complementary perspectives on the same problem can be fruitfully cross-leveraged.

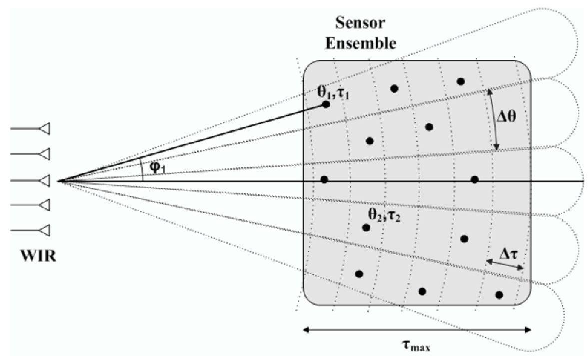


Fig. 1. Active Wireless Sensing: basic communication architecture.

The next section presents the basic space-time communication architecture in Active Wireless Sensing by exploiting connections with space-time multipath channels. Section 3 presents preliminary simulation results to illustrate the performance of Active Wireless Sensing. Section 4 provides a discussion of the results and concluding remarks.

2. THE BASIC SPACE-TIME COMMUNICATION ARCHITECTURE

Consider an ensemble of K sensors uniformly distributed over a region of interest, as illustrated in Fig. 1. We assume that the WIR, equipped with an M-element array, is sufficiently far from the sensor ensemble, in the same plane, so that far-field assumptions apply. The WIR interrogates the sensor ensemble by transmitting orthogonal (spread-spectrum) 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 $MN = MTW$.

2.1. The Multipath Channel in Active Wireless Sensing

We make the practically feasible assumption that the WIR and the sensor nodes are carrier (frequency) synchronized but not phase synchronized. Furthermore, we assume that the phase offset between each sensor and the WIR stays constant at least during the packet duration T. The basic communication protocol consists of the WIR transmitting the space-time signal $\boldsymbol{s}(t) = [s_0(t), s_1(t), \ldots, s_{M-1}(t)]^T$ in an interrogation packet to initiate information retrieval from the sensor ensemble. The i^{th} sensor receives a superposition of the transmitted waveforms

$$x_i(t) = \sum_{\mu=0}^{M-1} s_\mu(t - \tau_{i,\mu}) e^{-j\phi_{i,\mu}} \quad (1)$$

where $\tau_{i,\mu}$ is the relative (fixed w.r.t. to the antenna in the middle of the array) time-delay between the i^{th} sensor and μ^{th} antenna, $\phi_{i,\mu}$ is the corresponding relative phase offset, and we have assumed that the interrogation packet is transmitted with sufficient power (or is repeated enough) so that the noise in $x_i(t)$ is negligible.

In the far-field, and under appropriate choice of W ($\max_\mu \tau_{i,\mu} - \min_\mu \tau_{i,\mu} \ll 1/W$ for all i), the differences in the relative time delays between a given sensor and different WIR antennas can be neglected in the signaling waveform; that is, $s_\mu(t-\tau_{i,\mu}) \approx s_\mu(t-\tau_i)$, for all μ, where τ_i denotes the common delay from the i-th sensor to the WIR. The relative phase offsets in $x_i(t)$ due to different antenna elements $\{\phi_{i,\mu}\}$ consist of a common (random) component ϕ_i and a deterministic component that is captured by the steering/response vector of the array. For simplicity, we consider a one-dimensional uniform linear array (ULA) with spacing d and assume M to be odd WLOG, and define $\tilde{M} = (M-1)/2$. The array steering/response vector for a ULA is given by

$$\boldsymbol{a}(\theta) = \left[e^{j2\pi\tilde{M}\theta}, \ldots, 1, \ldots, e^{-j2\pi\tilde{M}\theta}\right]^T \quad (2)$$

where the normalized angle θ is related to the physical angle of arrival/departure φ (see Fig. 1) as $\theta = d\sin(\varphi)/\lambda$. The steering/response vector represents the relative phases across antennas for transmitting/receiving a beam in the direction θ. Thus, $x_i(t)$ can be compactly expressed as

$$x_i(t) = e^{-j\phi_i} \boldsymbol{a}^T(\theta_i)\boldsymbol{s}(t - \tau_i) \quad (3)$$

where θ_i denotes the direction of the i-th sensor relative to the WIR array (see Fig. 1). We assume $d = \lambda/2$ spacing, where λ is the wavelength of propagation, which corresponds to the sensor ensemble projecting maximum angular spread (180 degrees) at the WIR array; larger spacings can be used for smaller angular spreads.[1]

The i-th sensor encodes its measurement in β_i and modulates $x_i(t)$ by β_i and transmits it with energy $\mathcal{E}$ after a fixed duration (same for all sensors) following the reception of the interrogation packet. We assume instantaneous retransmission from each sensor for simplicity. Thus, the transmitted signal from the i-th sensor can be expressed as

$$y_i(t) = \beta_i \sqrt{\frac{\mathcal{E}}{M}} x_i(t) = \beta_i \sqrt{\frac{\mathcal{E}}{M}} e^{-j\phi_i} \boldsymbol{a}^T(\theta_i)\boldsymbol{s}(t - \tau_i) \quad (4)$$

[1] $d = \lambda/2\sin(\varphi_{max})$ spacing results is a one-to-one mapping between $\theta \in [-0.5, 0.5]$ and $\varphi \in [-\varphi_{max}, \varphi_{max}] \subset [-\pi/2, \pi/2]$.

where $|\beta_i| \leq 1$ and each $s_m(t)$ is of unit energy (so that $y_i(t)$ has energy $\mathcal{E}$). The received vector signal at the WIR, $\boldsymbol{r}(t) = [r_0(t), r_1(t), \ldots, r_{M-1}(t)]^T$, is a superposition of all sensor transmissions and by the principle of reciprocity it can be expressed as

$$\boldsymbol{r}(t) = \sqrt{\frac{\mathcal{E}}{M}} \sum_{i=1}^{K} \beta_i e^{-j\phi_i} \boldsymbol{a}(\theta_i)\boldsymbol{a}^T(\theta_i)\boldsymbol{s}(t - \tilde{\tau}_i) + \boldsymbol{w}(t) \quad (5)$$

where $\tilde{\tau}_i = 2\tau_i$ denotes the round-trip relative delay in the response from the i^{th} sensor, $\boldsymbol{w}(t)$ denotes an AWGN vector process representing the noise at different WIR antennas, and the random phase ϕ_i includes a random component due to reception at the WIR. Let $\tau_{max} = \max_i \tau_i$ and assume that $\min_i \tau_i = 0$ WLOG. Using (5), the effective system equation relating the received vector signal at the WIR to the transmitted interrogation signal can be expressed as

$$\boldsymbol{r}(t) = \sqrt{\frac{\mathcal{E}}{M}} \int_0^{2\tau_{max}} \boldsymbol{H}(t')\boldsymbol{s}(t - t')dt' + \boldsymbol{w}(t) \quad (6)$$

$$\boldsymbol{H}(t) = \sum_{i=1}^{K} \alpha_i \delta(t - \tilde{\tau}_i)\boldsymbol{a}(\theta_i)\boldsymbol{a}^T(\theta_i) \quad (7)$$

where $\alpha_i = \beta_i e^{-j\phi_i}$, and the $M \times M$ matrix $\boldsymbol{H}(t)$ represents the impulse response for the space-time multipath channel underlying Active Wireless Sensing. The delay spread of the channel is $2\tau_{max}$ and we assume that the packet signaling duration $T \gg 2\tau_{max}$. Note that the above system representation (6), even though it relates the transmitted interrogation signal $\boldsymbol{s}(t)$ to the received signal at the WIR, is independent of the power used for transmitting the interrogation packet. This is because after acquiring the signaling waveform in the interrogation phase, each sensor retransmits it with energy $\mathcal{E}$ and the factor $\sqrt{\mathcal{E}}/\sqrt{M}$ reflects this normalization.

2.2. Sensor Localization Via Multipath Resolution

The active sensing channel matrix (7) has exactly the same form as the impulse response of a physical multiple-antenna (MIMO) multipath wireless channel where the sensor data and phases $\{\alpha_i\}$ in the sensing channel correspond to the complex path gains associated with scattering paths in a MIMO multipath channel [4, 5]. A key motivation of this paper is to leverage insights from communication over multipath MIMO channels in the context of Active Wireless Sensing. In particular, we resort to the *virtual representation* of MIMO multipath channels that is a *unitarily equivalent* representation of the physical sensing/multipath channel matrix [4, 5]. A key property of the virtual channel representation is that its coefficients represent a resolution of multipath/sensors in angle and delay (and Doppler in case of relative motion, not considered in this paper) commensurate with the signal space parameters M and W (and T), respectively. The virtual representation in angle corresponds to beamforming in M fixed virtual directions: $\tilde{\theta}_m = m/M$, $m = -\tilde{M}, \cdots, \tilde{M}$. Define the $M \times M$ unitary (DFT) matrix

$$\boldsymbol{A} = \frac{1}{\sqrt{M}}[\boldsymbol{a}(-\tilde{M}/M), \ldots, 1, \ldots, \boldsymbol{a}(\tilde{M}/M)] \quad (8)$$

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 $\boldsymbol{H}_V(t)$ is unitarily equivalent to $\boldsymbol{H}(t)$ as

$$\boldsymbol{H}(t) = \boldsymbol{A}\boldsymbol{H}_V(t)\boldsymbol{A}^T \leftrightarrow \boldsymbol{H}_V(t) = \boldsymbol{A}^H\boldsymbol{H}(t)\boldsymbol{A}^* \quad (9)$$

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

$$H_V(m', m; t) = \boldsymbol{a}^H(m'/M)\boldsymbol{H}(t)\boldsymbol{a}^*(m/M) \quad (10)$$

$$= M\sum_{i=1}^{K}\alpha_i g\left(\theta_i - \frac{m'}{M}\right) g\left(\theta_i - \frac{m}{M}\right)\delta(t-\tilde{\tau}_i) \quad (11)$$

$$\approx \left[M\sum_{i\in S_{\theta,m}}\alpha_i g^2\left(\theta_i - \frac{m}{M}\right)\delta(t-\tilde{\tau}_i)\right]\delta_{m-m'} \quad (12)$$

where $g(\theta) = \frac{1}{M}\frac{\sin(\pi M\theta)}{\sin(\pi\theta)}$ is the Dirichlet sinc function that captures the interaction between the fixed virtual beams and true sensor directions, the last approximation follows from the virtual path partitioning due to beamforming in the virtual representation [4], δ_m denotes the kronecker delta function, and $S_{\theta,m} = \{i \in \{1, \cdots, K\} : -1/2M < \theta_i - m/M \leq 1/2M\}$ 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. Thus, the virtual spatial representation 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 $L = \lceil 2\tau_{max}W\rceil$ be the largest normalized relative delay. The diagonal entries of the virtual spatial matrix can be further decomposed into virtual, uniformly spaced delays as [5]

$$H_V(m, m; t) \approx \sum_{\ell=0}^{L} H_V(m, m, \ell)\delta(t-\ell/W) \quad (13)$$

$$H_V(m, m, \ell) = M\sum_{i=1}^{K}\alpha_i g^2\left(\theta_i - \frac{m}{M}\right)\text{sinc}(W\tilde{\tau}_i - \ell) \quad (14)$$

$$\approx \sum_{i\in S_{\theta,m}\cap S_{\tau,\ell}} M\alpha_i g^2\left(\theta_i - \frac{m}{M}\right)\text{sinc}(W\tilde{\tau}_i - \ell) \quad (15)$$

where $\text{sinc}(x) = \sin(\pi x)/\pi x$ captures the interaction between the fixed virtual and true sensor delays, and $S_{\tau,\ell} = \{i : -1/2W < \tilde{\tau}_i - \ell/W \leq 1/2W$ is the set of all sensors whose relative delays lie within the ℓ-th delay resolution bin of width $\Delta\tau = 1/W$. Thus, the angle-delay virtual representation partitions the sensor responses into distinct angle-delay resolution bins: the virtual coefficient $H_V(m, m, \ell)$ is a superposition of all sensor responses whose angles and delays lie in the intersection of m-th spatial beam and ℓ-th delay ring (see Fig. 1). For a given number of antennas M and for a given minimum spacing between sensors, the bandwidth W can be chosen sufficiently large, in principle, so that there is exactly one sensor in each angle-delay resolution bin (however this is not necessary as discussed later). In this 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 (15) that information retrieval from the i-th sensor amounts to estimating the corresponding virtual angle-delay coefficient

$$h_V(m, \ell) = H_V(m, m, \ell) \leftrightarrow M\beta_{i(m,\ell)}\gamma_{i(m,\ell)} \quad (16)$$

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

2.3. Information Retrieval Via Angle-Delay Beamforming

We now describe the basic signal processing at the WIR to estimate the virtual angle-delay coefficients $h_V(m, \ell)$ from the received signal $\boldsymbol{r}(t)$. Define $\boldsymbol{s}(t) = \boldsymbol{A}^*\boldsymbol{s}_V(t)$ and $\boldsymbol{r}_V(t) = \boldsymbol{A}^H\boldsymbol{r}(t)$ where $\boldsymbol{s}_V(t)$ and $\boldsymbol{r}_V(t)$ are the M-dimensional transmitted and received signals in the virtual spatial domain (beamspace). Using (6) and (9), the system equation (ignoring the fixed delay in re-transmission by the sensor nodes) that relates the received signal to the transmitted signal in the beamspace is

$$\boldsymbol{r}_V(m; t) \approx \sqrt{\frac{\mathcal{E}}{M}}\sum_{\ell=0}^{L} h_V(m, \ell)\boldsymbol{s}_V(m; t-\ell/W) + w(m; t) \quad (17)$$

where $\boldsymbol{r}_V(m; t)$ and $\boldsymbol{s}_V(m; t)$ denote the m-th components of $\boldsymbol{r}_V(t)$ and $\boldsymbol{s}_V(t)$, and $\{w(m; t)\}$ are ideally i.i.d. AWGN noise processes with PSD σ^2 but in practice will include interference from active sensors in other resolution bins. Recall that each $\boldsymbol{s}_V(m; t)$ is a unit-energy pseudo-random waveform with bandwidth W and duration T (e.g., a direct-sequence spread spectrum waveform) so that[2]

$$\langle \boldsymbol{s}_V(m, t-\ell/W), \boldsymbol{s}_V(m, t-\ell'/W)\rangle \approx \delta_{\ell-\ell'} \ . \quad (18)$$

Thus, correlating each $\boldsymbol{r}_V(m; t)$ with delay versions of $\boldsymbol{s}_V(m; t)$ yields the sufficient statistics for information retrieval

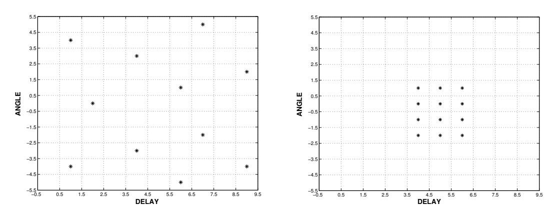
$$z_{m,\ell} = \langle \boldsymbol{r}_V(m, t), \boldsymbol{s}_V(t-\ell/W)\rangle \quad (19)$$

$$= \int_0^{T+2\tau_{max}} \boldsymbol{r}_V(m, t)\boldsymbol{s}_V(t-\ell/W)dt \quad (20)$$

$$\approx \sqrt{M\mathcal{E}}\beta_{i(m,\ell)}\gamma_{i(m,\ell)} + w_{m,\ell} \ , \quad (21)$$

where we have used (16) and $\{w_{m,\ell}\}$ are ideally i.i.d. Gaussian with variance σ^2 but in practice will include interference from other bins. Note that the factor $\sqrt{M}$ reflects the M-fold array gain or the beamforming gain associated with an M-element antenna array.

3. ILLUSTRATIVE NUMERICAL RESULTS



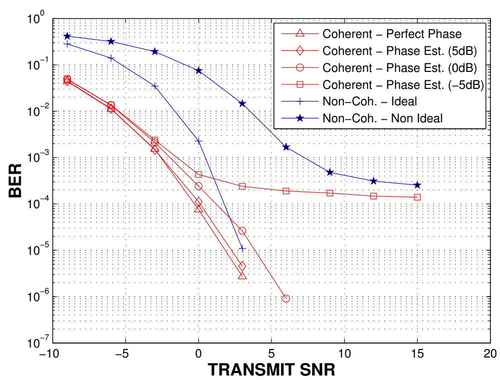
(a) (b)

Fig. 2. Angle-delay resolution bins for active sensors. (a) Multiple distributed events. (b) A single event in multiple co-located bins.

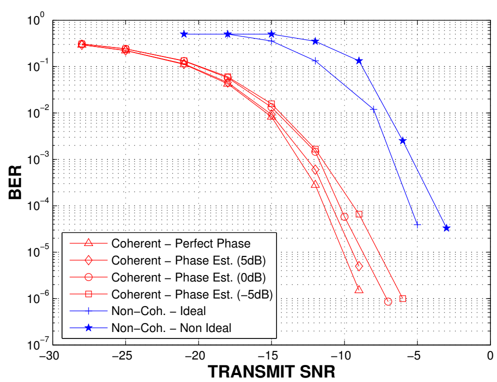
A single spread-spectrum waveform is used for all virtual spatial beams: $s_V(m; t) = q(t)$ for all m, where a length $N = 127$ pseudo-random binary code is used for $q(t)$. We consider both coherent (BPSK) and non-coherent (on-off) sensor transmissions. In the coherent case, we assume that the phases $\{\phi_i\}$ remain coherent over two packet intervals and each sensor transmits two bits for each information bit: a training bit from which the WIR estimates its relative phase, followed by the information bit. We consider $M = L = 11$ corresponding to a total of $ML = 121$ angle-delay resolution bins and illustrate the performance of Active Wireless Sensing in two extreme cases depicted in Fig. 2, involving $K = 11$ and $K = 12$ active sensors.

[2]The cross-correlation is on the order of $1/N = 1/TW$ and thus very small for large N.

The first case (Fig. 2(a)) represents 11 distributed events captured by sensors in distinct bins. Each sensor sends one bit of information to encode its measurement in each transmission. We assume that the distributed events are independent and for each event the sensor measurements are independent in different transmissions. Thus, the transmission bits are i.i.d. across sensors (space) as well as across time and a total of 11 bits are retrieved in each transmission interval. The correlator outputs of active bins[3] are independently processed to decode the corresponding sensor transmissions. The bit-error-rate (BER) as a function of the transmit SNR (per sensor) is shown in Fig. 3(a) for both coherent and non-coherent transmissions. The ideal non-coherent curve represents a benchmark in which the sensors are located at the center of the bins to minimize interference between sensors. All other BER plots involve averaging over random sensor locations within their bins to fully simulate interference. Non-ideal, non-coherent detection incurs a loss in SNR and also exhibits a BER floor of $\approx 2 \times 10^{-4}$ around 15dB due to interference. Remarkably, coherent detection performs quite well even in the presence of interference and for training SNR as low as 0dB.



(a)



(b)

Fig. 3. BER vs. SNR plots. (a) Independent sensor transmissions.(b) Identical sensor transmissions.

The second case (Fig. 2(b)) represents a single localized event observed by sensors in $K = 12$ adjacent bins. We expect the sensor measurements to be highly correlated (localized event) in this case and we simulate it by making all sensors transmit the same information bit sequence. Thus, a single bit of information is retrieved in each transmission period. The correlator outputs for active bins are coherently or non-coherently combined before making a decision. This case exhibits a dramatic improvement in BER compared to the first case due to the redundancy in sensor transmissions. Non-ideal non-coherent detection performs nearly as well as ideal non-coherent detection (no error floor) and coherent detection shows a 7dB gain over non-coherent detection reflecting the $K = 12$-fold SNR gain expected due to coherent combining of sensor transmissions at the WIR.

We note that analytical expressions for BER can be obtained for both cases using standard techniques [6] by approximating interference as Gaussian. However, the threshold needs to be optimized for the non-ideal non-coherent case. Details are omitted due to space.

4. DISCUSSION AND CONCLUSIONS

Active Wireless Sensing exploits MTW signal space dimensions in time, frequency and space for rapid and energy-efficient information retrieval from a sensor ensemble. In effect, a maximum of ML ($L \ll TW$) channels can be established for information retrieval by resolving sensors in angle and delay, which also gives a sensor localization map at a resolution commensurate with M and W. Transmissions from resolvable angle-delay bins are separated by using M dimensions (M beams and 1 spreading code). The remaining $M(TW - 1)$ dimensions can be exploited for increasing the rate and/or reliability of information retrieval.

The numerical results illustrate an inherent rate-reliability tradeoff in Active Wireless Sensing. The rate of information retrieval can be increased by sensing independent distributed events (Case I) through $N_c < ML$ sensing channels, although at the cost of reliability due to interference created by sensor location mismatch with fixed virtual beams. On the other hand, reliability can be dramatically increased by using all N_c channels for redundant localized sensing (Case II) at the cost of rate. Similarly, multiple correlated sensor transmissions from within each resolution bin can be exploited for reliability or power efficiency. We note that the power consumption in our numerical results can be significantly reduced by using independently coded transmissions from different sensors. A combination of these strategies can be used to optimize the rate-reliability tradeoff and energy efficiency in a given sensing task.

We have presented the basic communication architecture for Active Wireless Sensing in this paper. There are many exciting avenues for future work. We are currently developing low-complexity interference suppression strategies for increasing the reliability and energy-efficiency in high-rate information retrieval.

5. REFERENCES

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[3]The location of active bins can be reliably determined by the WIR by thresholding the correlator outputs in response to a training interrogation packet. The sensors respond to a training packet with a sufficiently long string of "1"'s to enhance the receive SNR at the WIR.