MAC-FREE READING OF A NETWORK OF CORRELATED SENSORS

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ABSTRACT

For dense wireless sensor networks (WSNs), the sensed information is typically spatially correlated, suggesting the use of cooperative transmission for energy efficiency. We propose a scheme where a large number of sensors cooperatively transmit to an airborne fusion center (node), such that the fusion is done automatically in the physical layer. The proposed scheme eliminates energy-inefficient control signaling for medium access control (MAC) and still performs well in terms of inverse normalized mean squared error (INMSE) of the estimated parameter function. The INMSE was evaluated via simulation as a function of various design parameters, including the average number of sensors per beam, degree of spatial correlation and the variance of the field values within the beam.

I. INTRODUCTION

A. Motivation

We assume a wireless sensor network (WSN) composed of a large number of simple, densely deployed sensors that have scarce energy resources. The sensors in a small area will observe common events. As a result, the sensed information is usually spatially correlated and energy could be saved using data fusion. Energy-efficient reading and fusion of the data from the sensor network is critical for the development of practical applications.

Most of the existing solutions for reading of a wireless sensor network require the use of medium access control (MAC) for forming sensor-clusters and coordinating wireless transmissions [1]. MAC involves control signaling which causes considerable overhead that consumes scarce energy resources [2,3,4]. A MAC-free scheme can be more energy efficient and have less delay as there is no contention for the channel.

The high energy cost of MAC and the inherent spatial correlation in wireless sensor networks suggest the use of *cooperative diversity* to reduce the energy cost by exploiting the spatial correlation of the sensed data. In this paper, a MAC-free cooperative scheme is proposed where the sensors cooperatively transmit to a fusion center (node) such that fusion is done automatically in the physical layer.

B. Network Setup and Proposed Scheme

In our scheme, an airborne fusion node transmits a synchronization pulse, which provides a possibly Doppler-shifted frequency reference for the sensor. The fusion node uses a directional antenna to ensure that only a limited number of sensors are illuminated at a time. Each sensor encodes its own information in the frequency of its transmission and transmits in response to the synchronization pulse, without coordinating with other sensor nodes. The fusion node receives a superposition of the sensor transmissions, which resembles a Doppler clutter spectrum in radar [5].

A similar approach is the opportunistic large array (OLA) [6], which is also proposed as a MAC-free scheme for cooperative transmission in sensor networks. In the OLA scheme, a leader node (a sensor) initiates the transmission and other nodes simply repeat the signal. Our scheme is different because the fusion node triggers the cooperative transmission and the cooperatively transmitting nodes do not all transmit the same signal.

The fusion node is airborne, which presents a different wireless channel compared to other previous works. The signal received at the fusion center contains a complex exponential signal part and a multiplicative noise part due to the simultaneous sensor transmissions. Such signal models have been investigated in [7] and [8] for jointly Gaussian multiplicative noise situations but the harmonic models have only included deterministic frequencies rather than random frequencies present in proposed scheme.

The network setup can be seen in Fig. 1, where the fusion node, ground sensors, and the footprint of the fusion node are shown. The beam is assumed to be pointing directly below the aircraft (mobile fusion node). The footprint is determined by the null-to-null beamwidth of the directional antenna used by the fusion node.

The sensors measure the scalar-valued field function $s(x,y)$ where (x,y) are the coordinates of a location in

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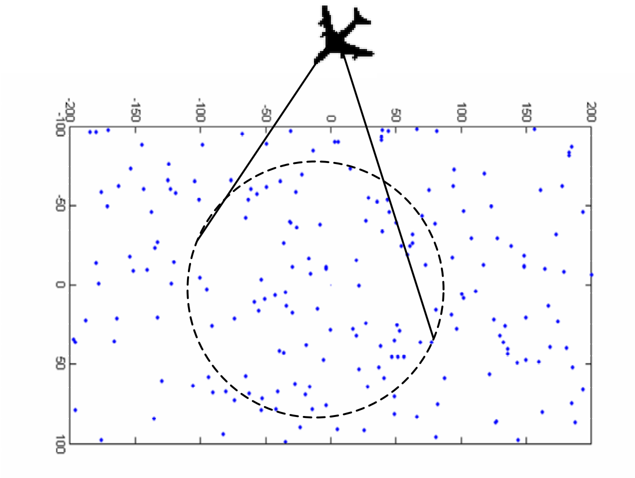

Figure 1. Sensor Network Setup with airborne fusion node and its beam footprint overlaid on ground sensors.

the field. Let $s_n=s(x_n,y_n)$ be the field value at the location of the nth sensor, then the RF frequency transmitted by sensor n can be simply formulated as

$$f = f_c + f_n + 2f_d \tag{1}$$

where f_c is the carrier frequency of the transmitted beacon, f_d is the one-way (i.e. air-to-ground or vice versa) Doppler frequency and f_n is the frequency offset which is a function of the sensed information s_n as follows:

$$f_n = hs_n + f_{\text{int}} \tag{2}$$

with modulation index h and intermediate frequency f_{int}.

The task of the fusion center is to estimate the field function $s(x,y)$ using the single reception channel output which is the superimposition of the transmissions from multiple sensors that fall in the beam footprint. In this paper, a low-complexity frequency-domain estimation algorithm and a subspace-based Multiple Signal Classification (MUSIC) algorithm [9] are compared for estimation of the parameter function over the sensor field. These algorithms are simulated for two different field functions: A deterministic field function (source) and a Gaussian distributed random process (source).

In the next section, statistical models for the fusion node reception will be introduced.

II. SIGNAL MODEL

As the fusion node is overhead, the signals from the sensors go through a line-of-sight (LOS) wireless channel, therefore the individual received amplitude from each sensor can be modeled with a simple path loss model. For the altitude and beamwidth BW we consider, the maximum variation by path loss inside a fusion node footprint is less than 1%.

A. *Modulation*

The antenna pattern is expressed below in (3) for sensor n where ϕ_n is the interrogator's look-down angle for this sensor. Such highly directional antenna patterns are possible with the use of linear array antennas and beamformers [9].

$$\alpha_n = \alpha(\phi_n) = \begin{cases} \left(\cos\left(\dfrac{\pi\phi_n}{BW}\right)\right)^{0.1} \; for \; \left|\dfrac{BW}{2}\right| > \phi_n \\ 0 \; for \; \left|\dfrac{BW}{2}\right| < \phi_n \end{cases} \tag{3}$$

With the mentioned parameters, the model for complex envelope $r(t)$ of the received signal by the fusion center can be expressed as

$$r(t) = \sum_{n=1}^{N} \alpha_n e^{j\Phi_n(t,f_n)} \tag{4}$$

where

$$\Phi_n(t,f) = 2\pi\left(2\frac{v}{\lambda}\sin\phi_n\cos\theta_n t + ft - b_n\right) \tag{5}$$

with antenna pattern amplitude α, aspect angle θ, look-down angle ϕ (angle between v_r and z in Fig. 2) and uniformly distributed random normalized phase b (between -1 and 1) for N transmitting sensors. For a single sensor, α, θ and ϕ all depend on the random x and y coordinates of the sensor's location. These angles are illustrated in Fig. 2.

Without loss of generality, setting $h=1$ and $f_{int}=0$, we express the received signal $r(t)$ as

$$r(t) = \left(e^{j2\pi s_c t}\right)\left(\sum_{n=1}^{N} \alpha_n e^{j\Phi_n(t,s_n-s_c)}\right) \tag{6}$$

where s_c is the scalar field value to be estimated. The second product term in (6) is the aforementioned multiplicative noise part of the received signal $r(t)$.

B. *Field Source Models*

The frequency used in transmissions is a function of the measured sensor value as introduced in (1). This paper investigates two different field source models: a deterministic scalar field and a Gaussian distributed random field.

In deterministic field model, the sensor measurement is a deterministic function of the Cartesian coordinates (x_n,y_n) of the sensor carrying out the measurement. For sensor n, the measurement in the deterministic field is

$$s_n = (ax_n + b)(ay_n + b) \tag{7}$$

where a and b are parameters that determine the particular shape of the field.

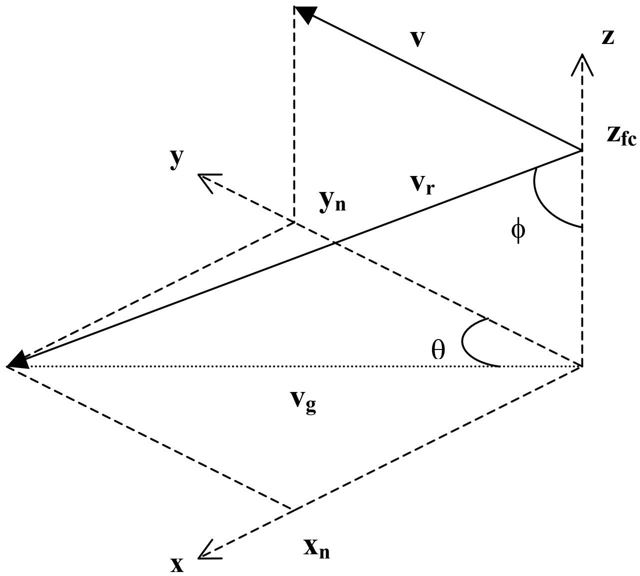

Figure 2. Fusion center - sensor geometry when fusion center is at (0,0,z_{fc}) and the sensor is at (x_n,y_n,0).

In the Gaussian distributed random field, the sensor measurements are jointly Gaussian random variables with distribution $N\left(0,\sigma_s^2\right)$ and covariance

$$Cov(s_i,s_j)=\sigma_s^2 e^{\frac{-d_{i,j}}{r_{corr}}} \quad (8)$$

which depends on the distance $d_{i,j}$ between two sensors i and j and the correlation radius r_{corr}. In other words, the correlation radius is a parameter to control the amount of spatial correlation in the field. Fields with lower values of r_{corr} have more correlation for a given distance.

III. ESTIMATION

The goal of the estimation process is to estimate the field function along the flight path at regular intervals as shown in Fig. 3 below. The distance between successive field values $s_c^n = s(x_c^n, y_c^n)$ to be estimated is exaggerated in this figure for demonstration. Each estimate is done using a window of M samples acquired from the sensors in the beam footprint transmitting in response to the beacon signal. The movement of the fusion node and beam footprint during the acquisition of the M samples is neglected since it is small in comparison to the beam footprint radius r_{ant}.

To estimate the field function $s(x_c, y_c)$ at the point (x_c, y_c) along the flight path, the fusion node records M samples such that the node is directly above point (x_c, y_c) midway through the window of M samples. These M samples are from the received signal that is the superposition of all the sensor signals in response to the beacon signal.

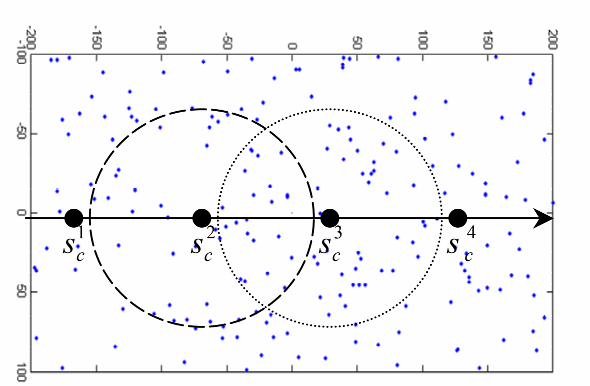

Figure 3. Sensor field including sensors and beam footprints (circles) for the estimation of s_c^2 and s_c^3 (Not to scale).

The error for a single estimate is defined as the difference of true field function (source) value s_c^n and the estimate $\hat{s}_c^n$ for that value. For a single trial in which a total of N_c estimates are made along the flight path, the MSE for the trial can be expressed as

$$MSE_{trial} = \frac{1}{N_c}\sum_{n=1}^{N_c}(s_c^n - \hat{s}_c^n)^2 \ . \quad (9)$$

The MSE for the whole Monte Carlo experiment is the average of trial MSE's over 300 trials. Error performance of two different estimation algorithms is simulated for both field parameter functions introduced earlier.

The first algorithm is a low-complexity frequency-domain algorithm that carries out a weighted average of the magnitude-squared values of the Fast Fourier Transform (FFT) of each window. Using the k^{th} FFT frequency ν_k and k^{th} FFT value $R(k)$, the estimate can be formulated as follows:

$$f_{est} = \frac{\sum_{k=1}^{M}\nu_k |R(k)|^2}{\sum_{k=1}^{M}|R(k)|^2} \quad (10)$$

The second estimation algorithm is the estimation of the main frequency in the window by the MUSIC algorithm with the assumption that the window contains one complex exponential. This estimation is done separately for each window.

In the following sections, the inverse normalized mean square error (INMSE),

$$INMSE = \frac{\sigma^2}{MSE}, \tag{11}$$

is used to compare the estimation schemes. σ^2 is the variance of the field function in the beam footprint and it is defined for each field function in the following section. The INMSE can be interpreted as a signal-to-noise ratio for the field function measurement.

IV. RESULTS

The simulated sensor field is a 200x300m field populated by a given number of sensors at random locations. The fusion node flies along the y-axis at a speed of 100m/s; thereby flying over the points *(0,100t)* during the simulation. The null-to-null beamwidth is 5 degrees. For each set of the results, 300 Monte Carlo trials were performed using window and FFT size of 256 and sampling frequency of 4kHz.

A. Deterministic Field Source

The field source used is a deterministic field source with $a=0.044$ and $b=22$. The σ^2 parameter in the INMSE is the squared maximum variance of the parameter function inside the beam footprint. Maximum variance is defined as the squared difference between the maximum and minimum values in fusion node's beam footprint.

The INMSE results with respect to the number of sensors in beam footprint (sensor density) can be seen below in Fig. 4 for the low-complexity frequency-domain estimation and MUSIC algorithms. The INMSE improves with increasing sensor density since there is a perfect correlation between sensor measurements and field parameter value to be estimated in deterministic field source.

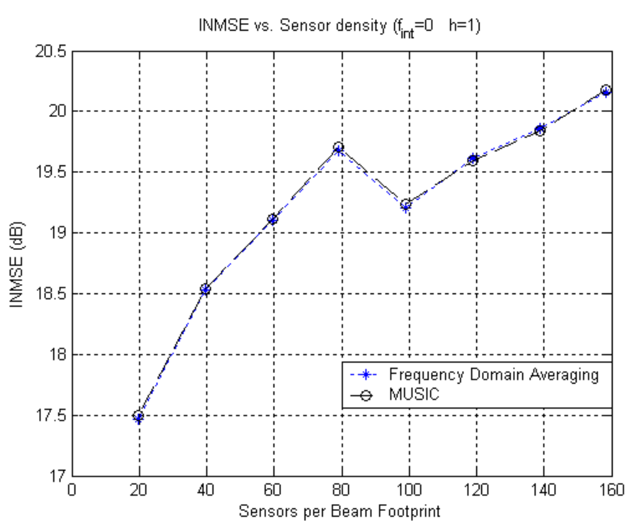

Figure 4. INMSE vs. Sensors per Beam Footprint is shown for deterministic field source.

B. Random Field Source

For the random field, the σ^2 parameter in the INMSE is the σ_s^2 which is the variance of the random variable obtained by sampling the field random process at a single point *(x,y)*.

Fig. 5 shows the INMSE against sensor density for $r_{corr}=1000m$ ($r_{corr}/r_{ant}=25$). The INMSE value has a steep increase for low values of sensor density because estimation windows contain no or very few sensors. The INMSE performance improvement saturates early to a stable value with high sensor densities as any further improvement is hampered by the amount of spatial correlation in the field.

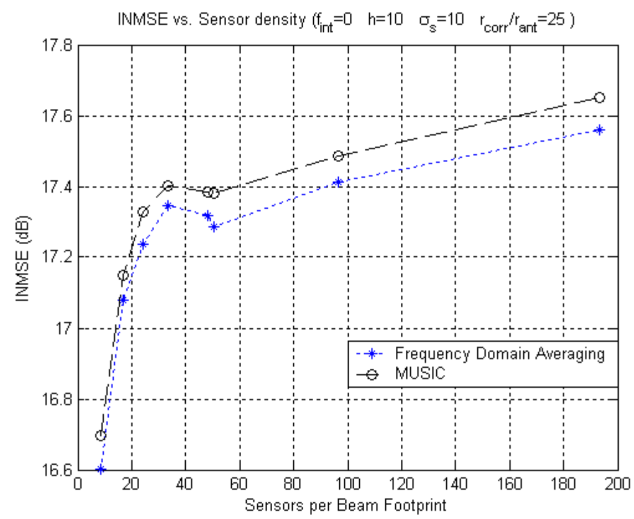

Figure 5. INMSE vs. Sensors per Beam Footprint is shown for random field source.

The $h\sigma_s$ product is an important parameter for this scheme when it's observed relative to the FFT frequency resolution $\Delta\nu = f_s/N_{FFT}$ with sampling frequency f_s and FFT size N_{FFT}. A larger $h\sigma_s$ product spreads the sensor signals in frequency domain resulting in more frequency-domain samples per estimate, thereby improving the estimate. Using $h\sigma_s > 6\Delta\nu$ gives satisfactory INMSE performance and increasing the $h\sigma_s$ product has diminishing returns after that point. The INMSE results in relation to the modulation index h are shown in Fig. 6 for the random field source case with $r_{corr}=1000m$ ($r_{corr}/r_{ant}=25$) and 400 sensors in the field (33 sensors per beam footprint on average).

The proposed scheme exploits the spatial correlation in the field; therefore, performance greatly depends on the amount of spatial correlation in the field. It is not a surprise that the correlation distance r_{corr} which controls the amount of spatial correlation in the field has a large impact on the performance of the scheme as seen in Fig. 8 for a

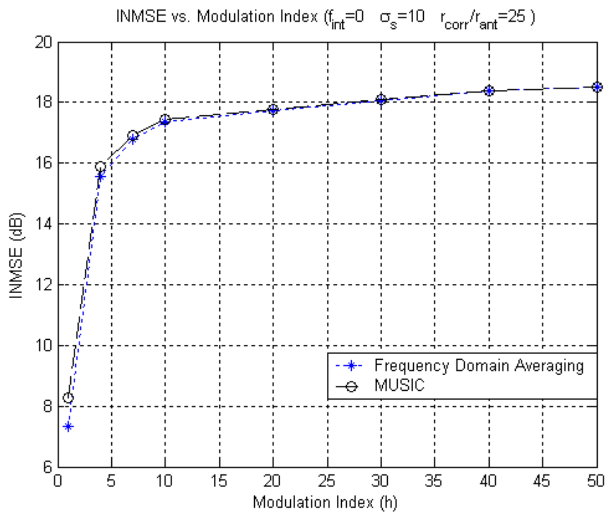

Figure 6. INMSE vs. modulation index (h) is shown for random field source.

field of 400 sensors (33 sensors per beam footprint on average). The system performance rapidly improves with higher spatial correlation and deteriorates with lack of correlation.

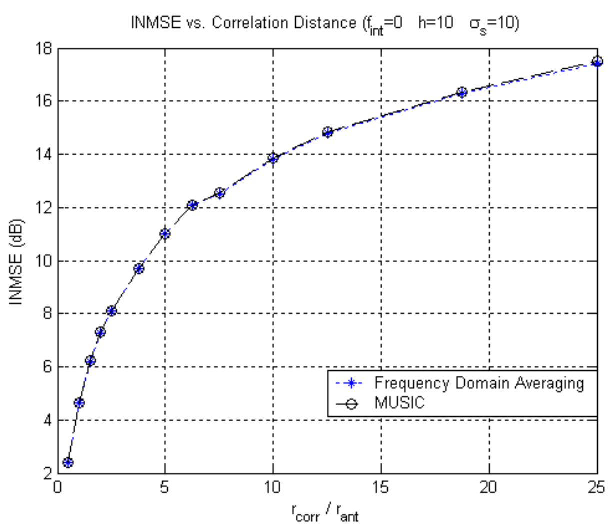

Figure 7. INMSE vs. correlation radius (r_{corr}) is shown for random field source.

V. CONCLUSIONS

The INMSE results demonstrate that the proposed scheme can be used to read a sensor network without the use of MAC. The proposed low-complexity frequency-domain estimation algorithm is a good initial approach as the comparison with subspace based estimation algorithm MUSIC shows, when its relative lack of complexity is considered. For future work, a scheme that processes larger regions of data similar to synthetic aperture radar will be considered.

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