Semi-Cooperative Spectrum Fusion (SCSF) for Aerial Reading of a Correlated Sensor Field

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***Abstract*—We present new theoretical results on the Semi-Cooperative Spectrum Fusion (SCSF) method of data fusion for spatially correlated information in wireless sensors. Data fusion exploits correlated sensed information to save scarce sensor energy by reducing the communication energy costs. SCSF eliminates Medium Access Control (MAC) and all data communication between sensors. In SCSF, a beacon is sent by the airborne collector through a directive antenna, and the illuminated sensors respond by simultaneously transmitting frequency modulated signals. The superposition of the sensor transmissions resembles a Doppler spectrum. The airborne collector (fusion center) applies a blind frequency estimator to the received superimposed signals for fusing the data. Estimation performance is evaluated in terms of the inverse normalized mean square error (INMSE) and is analyzed in terms of various system parameters such as sensor density, degree of correlation and modulation index. The analysis shows that the SCSF scheme performs well relative to a conventional fusion scheme that uses sample mean estimator for data fusion while not using MAC.**

I. Introduction

Some sensing applications, such as wildlife monitoring or sensor buoys on the ocean, take place outdoors, in approximately a two-dimensional plane, and in places where there is no wireless communications infrastructure. For such applications, reading the sensors by airplane or spacecraft may be the most convenient way. Dense sensor deployments may be desirable to provide redundancy as protection against loss of sensors. In dense deployments, the sensed data is likely to be correlated among clustered sensors. This paper analyzes a way to read a measurement from a cluster of sensors in one step- similarly to the way a Doppler radar takes a reading of a local area.

When the sensed information is spatially correlated, energy can be saved using data fusion [8], [9]. Most of the existing solutions for reading of a field of wireless sensors require the use of medium access control (MAC) for forming sensor-clusters and coordinating wireless transmissions [3]. These conventional schemes involve in-network fusion and the use of a multi-hop strategy to reach a sink or a base station. MAC signaling causes overhead that consumes considerable energy. Also in some environments such as underground or ocean surface, sensors are not able to easily communicate with each other, making exchange of MAC and data communication signals between sensors impractical. A MAC-free scheme can be more energy efficient and have less delay as there is no contention for the channel.

In this paper, a MAC-free scheme is proposed where the sensors simultaneously transmit their measured parameters to an airborne collector or reader when triggered by a beacon signal from the collector. The collector uses a directive antenna for transmitting the beacon signal so that only a cluster of nodes is illuminated. Each sensor in the illuminated cluster synchronizes to the beacon signal and immediately responds by transmitting a simple sinusoidal waveform which is frequency modulated (i.e. frequency shifted) by the sensor's reading. The airborne collector receives a superposition of these sinusoids, which resembles a Doppler spectrum [4]. The collector estimates the value of the parameter in the beam center from the measured spectrum.

The estimation of the sinusoid frequencies is similar to frequency synchronization in digital communication where maximum likelihood (ML) solutions make use of either data symbols or data symbol independence assumptions [13], which are not possible under our analog data assumption. More general ML solutions and Cramer-Rao bound (CRB) for estimating the individual sensor frequencies are tractable only in models with deterministic phase, amplitude and frequency [7]. In addition, these ML solutions are still inefficient and the approximate ML solution, which is picking the largest spectrum peak, is used when the time window available for estimation is very large [7]. Another frequency estimation algorithm developed with the assumption of a sinusoidal signal that has deterministic phase, amplitude and frequency, is the Multiple Signal Classification Algorithm (MUSIC) [6]. [12] looks at frequency estimation of a complex exponential under multiplicative and additive noise which are both Gaussian processes. The proposed solution is the cyclic estimator which is shown to be the nonlinear least squares estimator and is equivalent to peak-picking in the frequency domain [12].

Because the simultaneous sensor transmissions resemble a form of cooperative transmission called the Opportunistic Large Array (OLA)[5], we call our method Semi-Cooperative Spectrum Fusion (SCSF). SCSF differs from the OLA as follows. The function of an OLA is to simply relay a digitally modulated signal and therefore all nodes in an OLA transmit the same message. In contrast, nodes responding to a

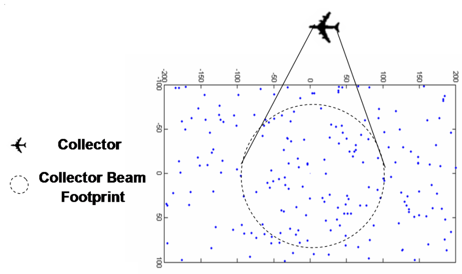

Fig. 1. Sensor Network Setup with airborne collector and its beam footprint overlaid on ground sensors.

SCSF beacon each transmit a different but correlated analog-modulated signal.

SCSF was first introduced in [1] with performance simulations. In this paper, we introduce new theoretical performance results on SCSF. Specifically, the new contributions in this paper are (1) showing that with the negligible Doppler effect and long observation interval assumptions, the power spectral density of the received signal at the reader is proportional to the probability density function (PDF) of the parameter values within the beam, given the true value of the parameter at the center of the beam, (2) that the mean of the conditional PDF is the sample mean of the sensor readings, assuming a flat-top collector antenna pattern, and (3) bounds on the modulation index to guarantee the best estimation performance.

Similar schemes with beacons have been suggested by [10] and [11]. In [10], the sensors amplitude modulate their signals using their measured data. MAC signals and other control signals are required to establish phase synchronization between sensors. The frequency modulation of our scheme eliminates the need for phase synchronization. In [11], sensors are read one-by-one using a pencil beam where the sensors modulate the beacon signal from the collector. Our approach instead both eliminates the MAC and accesses all sensors in the beam simultaneously.

II. Signal Model

In SCSF, the airborne collector transmits a synchronization pulse, which provides a possibly Doppler-shifted frequency reference for the sensors on the ground. The collector uses a directional antenna to ensure that only a limited number of sensors are illuminated at a time. Each sensor synchronizes to the frequency reference and then immediately transmits, encoding its own information by shifting the frequency of its transmission relative to the reference. There is no coordination with other sensor nodes. The collector receives a superposition of the sensor transmissions.

The network setup can be seen in Figure 1, where the airborne collector, the ground sensors and the beam footprint of the collector beacon are shown. The aircraft is assumed to be flying parallel to the ground with speed v. The beam is assumed to be pointing directly below the aircraft. The footprint is defined as the null-to-null beamwidth of the collector antenna.

The sensors measure the scalar-valued field function $s(x,y)$ where (x,y) are the coordinates of a location in 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 f'_n received from sensor n can be simply formulated as

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

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 depends on the sensed information s_n according to

$$f_n = hs_n + f_o \tag{2}$$

with modulation index h and offset frequency f_o.

The sensed information, s_n, is a sample from a Gaussian distributed random field. More specifically, the sensor measurement vector $\underline{s} = [s_1, s_2, .., s_n]$ contains jointly Gaussian random variables with joint distribution $N(0, C)$. The covariance matrix C has diagonal entries of σ_s^2 and non-diagonal entries of

$$C_{ij} = \sigma_s^2 exp\left(\frac{-d_{i,j}}{r_{corr}}\right), \tag{3}$$

which depends on the distance $d_{i,j}$ between two sensors i and j and the correlation radius r_{corr}. The correlation radius is a parameter that represents the amount of spatial correlation in the field. Fields with higher values of r_{corr} have more correlation for a given distance.

The task of the collector is to estimate the field function $s_c = s(x_c, y_c)$ directly below the collector (at (x_c, y_c)) using the single reception channel output, which is the superimposition of the transmissions from multiple sensors that fall in the beam footprint. Different estimation schemes can be employed in the SCSF approach. We consider the simple SCSF-Spectrum Mean approach that estimates the spectrum as a periodogram [6], normalizes the periodogram area and then finds its mean, as though the normalized periodogram were a probability density function (PDF). We also consider SCSF-MUSIC which applies the subspace-based Multiple Signal Classification (MUSIC) algorithm [6] to the received SCSF signal. We will compare these two SCSF versions to the sample mean of the sensed data, which could be produced by having cluster head poll the sensors using a MAC.

As the collector is above a sensor field, the signals go through a line-of-sight (LOS) wireless channel; therefore, the individual received amplitude from each sensor follows a simple path loss model. For the altitude of $2km$ and beamwidth of 2.5^o (BW) that we consider, the maximum variation of the path loss inside a collector footprint is less than 1%. The antenna pattern for sensor n, α_n is $(cos(\frac{\pi\phi_n}{BW}))^{0.5}$ over the beamwidth, and zero outside the beamwidth. ϕ_n is the collector's look-down angle for sensor n, as shown in Figure 2. Such highly directional antenna patterns are possible with the use of phased array antennas and beamformers [6] which have been widely used in aircraft of all sizes [4].

With the mentioned parameters, the model for the complex envelope $g(t)$ of the received signal by the collector can be

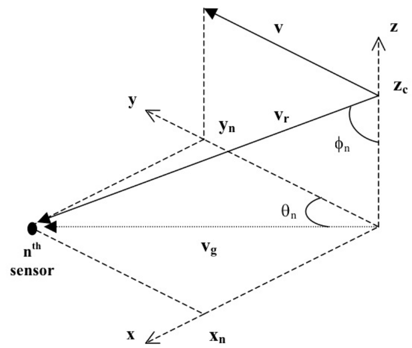

Fig. 2. Collector-sensor geometry when the collector is at $(0, 0, z_{fc})$ and the sensor is at $(x_n, y_n, 0)$.

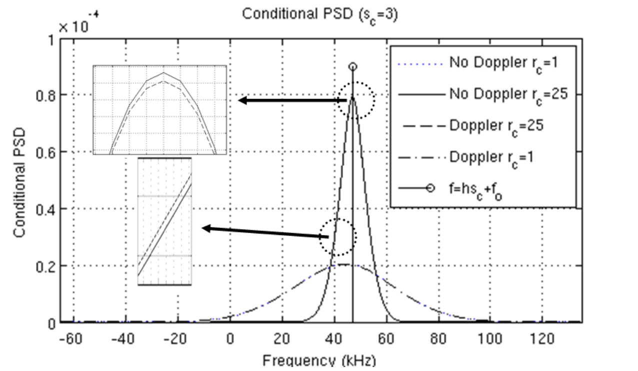

Fig. 3. Conditional PSD with the s_c=3 and modulation index of 2400, $r_c = r_{corr}/r_{ant}$ The blow-up of the peak shows the minor distinction between Doppler or Doppler-neglected Conditional PSDs ($f_o = 40kHz$, z_c=2000m, N_o=0, r_{ant}=40m)

expressed as

$$g(t) = \sum_{n=1}^{N} \alpha_n exp(j\Phi_n(t, f_n)) + n(t) \quad (4)$$
$$with \quad \Phi_n(t, f) = 2\pi(4\frac{v}{\lambda}sin\phi_n cos\theta_n t + ft - b_n),$$

where λ is the wavelength corresponding to the carrier frequency f_c, θ_n is the aspect angle and b_n is a uniformly distributed (between -1 and 1) random normalized phase for the n^{th} transmitting sensor. The first frequency term in $\Phi_n(t, f)$ is the two-way Doppler offset $2f_d$. The random phase represents the phase responses of the sensor antennas and RF front ends, the carrier phase differences caused by the different sensor-reader distances, and intentional random phase offsets that might be inserted at the sensors. The receiver thermal noise $n(t)$ is complex additive white gaussian noise (AWGN) independent from all other parameters. For a single sensor, α, θ and ϕ all depend on the random x and y coordinates of the sensors's location.

We propose a simple estimation approach based on the conditional power spectral density (PSD) $S_g(\nu|s_c)$ of the received signal $g(t)$ given the true value, s_c, of the field parameter in the center of the beam footprint. Assuming $\alpha_n = 1$ for all n and finite-time window effects, the PSD, conditioned on the value, s_c, of the field in the beam center, can be shown to be [2]

$$S_g(\nu|s_c) = N \int_{\theta=-\pi}^{\pi} \int_{\phi=0}^{tan^{-1}\left(\frac{r_{ant}}{z_c}\right)} f_\theta(\theta) f_\phi(\phi)$$
$$f_{s|s_c,\phi,\theta}\left(\frac{\nu - f_o - 2f_d}{h}\middle| s_c, \phi, \theta\right) d\theta d\phi + N_o. \quad (5)$$

where $f_{s|s_c,\phi,\theta}(s|s_c, \phi, \theta)$ is the conditional Gaussian PDF for the value s of the sensor field at an elevation ϕ and angle θ as described in Fig. 2. The conditional PDF has mean $s_c e^{\frac{-z_c tan(\phi)}{r_{corr}}}$ and variance $\sigma_s^2 \left(1 - e^{\frac{-2z_c tan(\phi)}{r_{corr}}}\right)$.The integral is averaging over the possible values of ϕ and θ assuming that the point s is selected at random on a disc of radius r_{ant}. Therefore, θ has a uniform distribution whereas ϕ is distributed as $f_\phi(\phi) = C \tan\phi \sec\phi^2$ with constant C.

Figure 3 shows conditional PSDs for the case of $s_c = 3$ for high ($r_{corr} = 25r_{ant}$) and low ($r_{corr} = r_{ant}$) correlation of sensed data with and without the Doppler effects. The stem shows the frequency corresponding to the true value s_c. We observe that the effect of Doppler spread on the conditional spectrum is very minor. Since the Doppler effect is negligible, we drop the Doppler frequency f_d, and observe that if $\frac{\nu - f_o}{h}$ is replaced by s in (5), then the integrand is the conditional joint PDF, $f(s, \phi, \theta|s_c)$. The result of the integral will be the conditional PDF of s, given s_c. The interpretation of this conditional PDF is that it is the value of the field at some random location within the beamprint, given that the value in the center of the beamprint is s_c.

Next, we can define the random variable ν as a simple affine function of s, $\nu = g(s) = hs + f_o$ and derive the conditional PDF of ν, conditioned on s_c. Substituting into (5) yields $S_g(\nu|s_c) = Nhf_\nu(\nu|s_c)$. This shows us that if we neglect noise and Doppler effects, $S_g(\nu|s_c)$ can be interpreted as a scaled version of the conditional PDF of ν within the beamprint, given only the value of the field in the beam center.

III. Estimation

The goal of the estimation process is to estimate values $s_c^m = s(x_c^m, y_c^m)$ along the flight path at regular intervals. The spatial sampling rate should be at least at the spatial Nyquist sampling rate for the field [2].

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

$$INMSE = \frac{\sigma_s^2}{MSE} \quad (6)$$

is used to compare the estimation schemes. Normalized MSE has been used as a metric for the estimator performance [6]. When evaluating estimators, it is important to normalize the MSE, because otherwise there can be no sense of good or bad values. For example, an MSE of $1,000$ might represent excellent performance if the range of possible values is 10^7. The INMSE can be interpreted as a signal-to-noise ratio for the field function measurement.

A. Semi-Cooperative Spectrum Fusion (SCSF) Estimators

In the two SCSF schemes, the measurement vector $\underline{s}$ is not available. Instead a superposition of the transmitted waveforms from each sensor is available. To estimate the field function $s_c = s(x_c, y_c)$ at the point (x_c, y_c) along the flight path, the collector records N_{win} samples such that the node is directly above point (x_c, y_c) midway through the window of N_{win} samples. These N_{win} samples are from the received signal that is the superposition of all the sensor signals in response to the beacon signal. The movement of the collector and beam footprint during the acquisition of the N_{win} samples is neglected in our analysis since it is small in comparison to the beam footprint radius r_{ant}, however, Doppler effects are still included via (4).

The SCSF method estimates s_c from the Discrete Fourier Transform (DFT) of the N_{win} samples. Using the k^{th} DFT frequency ν_k and k^{th} DFT value $G(k)$, the SCSF-Spectral Mean (S-SM) estimate can be formulated as

$$\hat{s}_{c,S-SM} = \frac{1}{h}\frac{\sum_{k=1}^{N_{win}} \nu_k |G(k)|^2}{\sum_{k=1}^{N_{win}} |G(k)|^2} - f_o \tag{7}$$

Directly analyzing (7) is difficult since $G(k)$ involves a superposition of sincs. Instead, if the Continuous Fourier Transform $G(\nu)$ is taken over an infinite time-window, and negligible Doppler effects and a unitary antenna pattern ($\alpha_n = 1$) are assumed, an approximation for the estimator becomes

$$\hat{s}_{c,S-SM} = \frac{1}{Nh}\int_{-\infty}^{\infty}\sum_{n=1}^{N} \nu\delta(\nu - f_n)d\nu - f_o \tag{8}$$

$$\hat{s}_{c,S-SM} = \frac{1}{Nh}\left(\sum_{n=1}^{N} f_n\right) - f_o \tag{9}$$

for high communication SNR, i.e. N_o=0. This is equal to the sample mean estimator (sme) $\hat{s}_{c,sme} = \frac{1}{N}\sum_{n=1}^{N} s_n$ which shows that the sample mean estimator is an approximation for the SCSF-Spectral Mean estimator.

The second SCSF algorithm simulated is the SCSF-MUSIC algorithm, which estimates the main frequency in the time window using the MUSIC algorithm with the assumption that the time window contains only one complex exponential.

B. Sample Mean Estimator MSE_{sme}

A MAC-aided network explicitly uses the vector of sensor measurements $\underline{s}$ for data fusion to calculate the Sample Mean Estimator directly. The Sample Mean Estimator is optimal in terms of Mean Squared Error when the covariance matrix C is not available [6].

The MSE for the sample mean estimator in terms of the correlation radius r_{corr} and number of sensors N could be acquired by conditioning over sensor positions and then replacing sensor positions with expressions for distances between sensors. Using the correlation model of (3) and that the sensor locations and intersensor distances are identically distributed, the normalized MSE simplifies to [2]

$$\frac{MSE_{sme}}{\sigma_s^2} = \frac{N+1}{N} + \frac{N-1}{N}E_{d_{ij}}\left[e^{\frac{-d_{ij}}{r_{corr}}}\right] - 2E_{d_{ci}}\left[e^{\frac{-d_{ci}}{r_{corr}}}\right]. \tag{10}$$

where the first expectation is averaging over the distances between a randomly chosen pair of sensors and the second expectation averages over the distance from the beam center to a random sensor location. The expectation in the third term simplifies to

$$E_{d_{ci}}\left[e^{\frac{-d_{ci}}{r_{corr}}}\right] = 2\left(\frac{r_{corr}}{r_{ant}}\right)^2\left(1 - \left(1 + \frac{r_{ant}}{r_{corr}}\right)e^{-\frac{r_{ant}}{r_{corr}}}\right) \tag{11}$$

whereas the expectation in the second term is evaluated through numerical integration [2].

C. Lower Bound (h_{min}) for SCSF-Spectral Mean

As the modulation index h is a design parameter, a too-low h will imply that the measured spectrum will not be adequately sampled. Since there are a finite number of frequency bins in the DFT $G(k)$, there is some quantization noise in frequency points. The mean squared error that results from this quantization noise of using discrete frequency bins is expressed as

$$MSE_Q = \frac{1}{h^2}\frac{1}{12}\Delta\nu^2 = \frac{1}{12}\left(\frac{f_s}{hN_{win}}\right)^2 \tag{12}$$

in terms of frequency resolution $\Delta\nu$, sampling frequency f_s and FFT size N_{win}. Assuming that the quantization noise is negligible when it is 1 order of magnitude or 10dB smaller than the sample mean estimator (sme) MSE, the lower bound becomes

$$h_{min} = \sqrt{\frac{10}{12}MSE_{sme}}\frac{f_s}{N_{win}}. \tag{13}$$

D. Upper Bound (h_{max}) for SCSF-Spectral Mean

The upper bound for the modulation index occurs when the modulation index causes aliasing. This happens when sensors transmit at frequencies outside the band $(\frac{-f_s}{2} < \nu < \frac{f_s}{2})$, which alias. As a result of this alias, the frequency ν that is reported aliases to $\nu_A = \left[\left(\nu + \frac{f_s}{2}\right) \; mod \; f_s\right] - \frac{f_s}{2}$ causing an error of $\nu - \nu_A$ in the estimation process. Therefore, the MSE_A from aliasing is $\frac{1}{h^2}E\left[(\nu - \nu_A)^2\right]$ where ν is treated as a random variable whose PDF is given by the conditional power density spectrum (5). The upper bound for modulation index h_{max} is defined as the value when the MSE_A approaches one tenth of the MSE without aliasing. After plugging in the marginal distribution $f_{s_c}(s_c)$ for s_c, we can evaluate MSE_A as

$$MSE_A = \frac{1}{h^2}\int_{s_c=-\infty}^{\infty}(\nu - \nu_A)^2 f_{s_c}(s_c)S_g(\nu|s_c)ds_c. \tag{14}$$

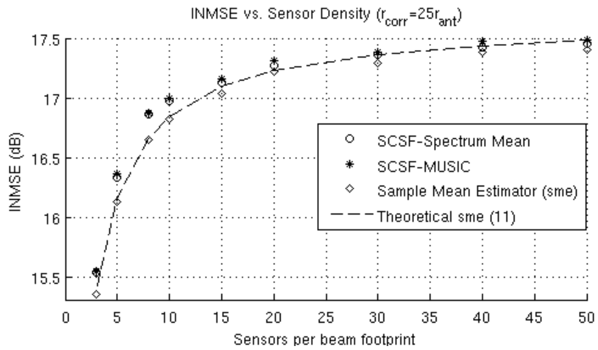

Fig. 4. Performance Results for varying sensor density, $r_{corr} = 25r_{ant}$, $f_s = 512kHz$, $N_{win} = 256$.

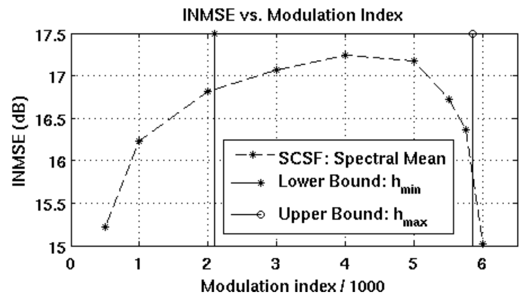

Fig. 5. INMSE with overlaid bounds on Modulation Index h.

IV. RESULTS

Let a single trial correspond to a total of M estimates that are made along the flight path. The error for the mth estimate is defined as the difference of true field function (source) value s_c^m and the estimate $\hat{s}_c^m$ for that value. Then, the MSE for the trial can be expressed as

$$MSE_{trial} = \frac{1}{M}\sum_{m=1}^{M}(s_c^m - \hat{s}_c^m)^2 \quad (15)$$

The MSE for the whole Monte Carlo experiment is the average of trial MSE's over 5,000 trials using FFT size of 256 and sampling frequency of 512kHz. The footprint radius is 40m and the collector flies at a speed of 100m/s. Figure 4 shows the INMSE versus N, the number of the sensors in the beam footprint for three different estimators and for the theoretical result in (10). From (10), we expect the INMSE to converge as the number of sensors per beam, N, becomes large, which is observed in Figure 4. The performance increase after $N = 10$ is minor. As suggested by (9), the SCSF-Spectral Mean performance is approximately equal to the sample mean estimator performance.

SCSF estimators perform a little better than the sample mean estimator most likely due to the additional weighing of highly correlated sensor measurements by the antenna pattern. The SCSF-Spectral Mean performs very closely to SCSF-MUSIC algorithm, which suggests that the SCSF-Spectral Mean approach should be preferred because of its simplicity.

Figure 4 also shows that (10) is in approximating the INMSE as a function of the correlation distance. The INMSE increases significantly with the correlation radius r_{corr}, as expected from (10), however the increase is gradual, and a value of r_{corr} of at least 15 times the radius of the beamprint is necessary to get the INMSE above 15dB. For the $40m$ beam footprint radius, this requires a correlation radius of $600m$.

As shown in Figure 5, the derived lower and upper modulation index bounds h_{min} and h_{max} are effective at defining a range for the modulation index. The INMSE is within 1.5dB of the peak value inside this range. At $h = h_{max} + 300$, the INMSE is already 3dB worse, and at $h = h_{min} - 1000$, the INMSE is 2dB worse from the peak value.

V. CONCLUSION

The INMSE results have demonstrated that the SCSF scheme can be used to read a field of correlated wireless sensors from an aircraft flying overhead without the use of a MAC. The two proposed SCSF algorithms perform closely to the alternative conventional MAC-aided network protocol in terms of INMSE. The normalized power spectral density of the signal received at the reader, assuming a long observation time and conditioned on knowing the field value in the center of this beam, was shown to be proportional to the probability density function of the beam-illuminated field value conditioned on the value in the center of the beam. SCSF-Spectral Mean estimation performance could possibly be further improved through the use of training. The general SCSF technique is also useful to read parameters from any distant cluster of radios in a LOS environment.

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