A New Ultra-Low Power Wireless Sensor Network with Integrated Energy Harvesting, Data Sensing, and Wireless Communication

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***Abstract*— A new ultra-low power (ULP) wireless sensor network (WSN) structure is proposed to monitor the vibration properties of civil structures, such as buildings and bridges. The new scheme integrates energy harvesting, data sensing, and wireless communication into a unified process, and it is fundamentally different from all the existing WSNs. In the new WSN, piezoelectric sensors are employed to harvest vibration energy and measure vibration intensity simultaneously, by utilizing the fact that *the harvested energy accumulated through time is proportional to the vibration amplitude and frequency*. Once the harvested energy reaches a threshold, it is released as an impulse with a wireless transmitter. An estimate of the structure vibration intensity can then be obtained by measuring the intervals between the binary impulses. Such an approach does not require complicated analog-to-digital conversion or signal processing, and it can achieve an ULP performance unrivaled by existing technologies. Optimum and sub-optimum impulse density estimation algorithms are proposed to take advantage of the spatial correlation among the sensors. Exact analytical expressions of the optimum estimation mean square error (MSE) are derived. Simulation and analytical results demonstrate that the proposed scheme can achieve a MSE of 5×10^{-5} at a signal-to-noise-ratio of -8 dB for a 10-node WSN.**

I. INTRODUCTION

Wireless sensor network (WSN) designed for structure health monitoring (SHM) is expected to operate uninterrupted over years or decades, under the constraints of extremely limited battery capacity or small energy scavenging devices. Hence, an extremely stringent power budget is required to power the operation of a wireless sensor, which transmits the measured data to a fusion center (FC) through a wireless link.

Recently there have been considerable efforts devoted to the development of WSN for SHM systems [1] – [5]. Most of the sensing systems are built with commercial-off-the-shelf (COTS) wireless sensor nodes, such as Mica-Z Mote [2], [3], Mica-2 Mote [4], and iMote [5], etc. Even though these modules are designed with low power consumption as one of the design objectives, their structures still follow a conventional sensing framework, which includes sensing, analog-to-digital conversion (ADC), digital signal processing (DSP), and wireless transmission. These modules are designed separately, and they do not directly take advantage of the unique features of SHM systems. In order to achieve ULP performance, we need to break free from the conventional sensing frameworks, and seek fundamentally new WSN structures.

In this paper, we propose a new type of battery-free ULP WSN by integrating energy harvesting, data sensing, and wireless communication into a unified process. The system is designed to monitor the structure vibration intensity, such as vibration amplitude and frequency, which provide useful information about the local stress intensity and the dynamic behaviors of the structure [6]. Vibration generates energy that can be harvested by a sensor with piezoelectric devices [7]. The harvested energy is expected to power the operations of the entire sensor node. However, due to the low efficiency of current piezoelectric materials, the harvested energy level is usually much lower compared to that required to perform any regular sensing, ADC, DSP, or communication functions. Therefore, conventional sensing or communication techniques can no longer be applied in such a system.

We propose to address this problem by utilizing the correlation between energy and vibration, *i.e.*, the harvested energy accumulated through time is proportional to the local vibration amplitude and frequency. Once the harvested energy reaches a predefined threshold, the energy is released in the form of an impulse. The receiver can then obtain an estimate of the vibration intensity by observing the impulse density, *i.e.*, the number of impulses in unit time. Such an integrated harvesting, sensing, and communication (IHSC) process exploits the unique features of a SHM system, and it is fundamentally different from conventional sensing schemes. Optimum estimation algorithms based on the maximum *a posteriori* (MAP) criterion are proposed to extract the impulse density at the FC by utilizing the correlation among the spatially distributed sensors. Exact analytical expressions of the estimation mean square error (MSE) are derived to predict the performance of the proposed system. A sub-optimum impulse density estimation algorithm base on spatial MAP is presented to balance the tradeoff between complexity and performance. Both simulation results and theoretical analysis show that the proposed ULP WSN scheme can operate effectively at the ULP regime.

II. A NEW WSN STRUCTURE WITH INTEGRATED HARVESTING, SENSING, AND COMMUNICATION

Consider a WSN consisting of a large number of low cost battery-free wireless sensor nodes uniformly distributed over the monitored structure. Each sensor node is equipped with a piezoelectric sensor for energy harvesting and data sensing, and a simple radio frequency (RF) transmitter, such as a simple resistor-capacitor (RC) oscillator. The sensor performs the IHSC operation as follows.

Definition 1 (IHSC): The energy collected by the piezoelectric sensor is used to charge a capacitor. Once the harvested energy reaches a predefined threshold, E_{TH}, the energy is

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released as a single impulse through the RF transmitter. Then the receiver can obtain an estimate of the structure vibration intensity by measuring the impulse density. ■

In the above IHSC procedure, it is assumed that the energy harvesting rate, *i.e.*, the energy harvested in unit time, is proportional to the structure vibration intensity, such as vibration amplitude and frequency. As a result, the amount of time required for the harvested energy to reach E_{TH} is inverse proportional to the vibration intensity. Therefore, the structure vibration information is carried in the form of the time delay between two consecutive impulses, or the number of impulses in unit time. The proposed IHSC scheme utilizes the correlation among structure vibration, energy, and time to get an estimate of the structure vibration intensity.

Given the fact that the structure vibration is highly correlated across the spatial domain, the density information collected by spatially distributed sensors is correlated. Such correlation information can be exploited by the FC to increase the estimation accuracy even at extremely low signal-to-noise ratio (SNR). Optimum and sub-optimum impulse density estimation algorithms will be developed in the following sections to exploit the spatial correlation among sensors.

To facilitate analysis, we have the following assumptions regarding the statistical properties of the structure vibration.

A.1) The amount of time for the harvested energy to reach E_{TH} is an exponentially distributed random variable (RV) with mean μ. A higher vibration intensity yields a smaller μ.

A.2) The time is discretized into small intervals with duration $T_s << \mu$. For each interval, the receiver performs detection to find whether there is an impulse in the interval. Define a RV, $x_n(k)$, where $x_n(k) = 1$ represents an impulse is transmitted by the node n at the k-th detection interval and 0 otherwise. Based on Assumption A.1), it can be easily shown that $x_n(k)$ is a Bernoulli RV with the parameter

$$\gamma = P(x_n(k) = 1) = 1 - e^{-\frac{T_s}{\mu}}. \tag{1}$$

A.3) Data collected from different sensor nodes are correlated. The vibration correlation is translated to the correlation among the Bernoulli RVs, $\{x_n(k)\}_{n=1}^N$. The normalized correlation coefficient between $x_m(k)$ and $x_n(k)$ is

$$\phi_{mn} \triangleq \frac{\mathbb{E}\{[x_m(k) - \bar{x}_m(k)][x_n(k) - \bar{x}_n(k)]\}}{\sqrt{\sigma_m^2 \sigma_n^2}} = \theta^{|m-n|}, \tag{2}$$

where $\theta \in [0, 1]$ is the spatial correlation coefficient, $\bar{x}_m(k)$ is the mean of $x_m(k)$, σ_m^2 is the variance of $x_m(k)$ and $\mathbb{E}(\cdot)$ is the expectation operator.

A.4) Sensors deliver the impulses to the FC through an orthogonal media access control (MAC) scheme, such as the frequency division multiplexing access (FDMA), to achieve a collision-free communication at the FC.

With the above assumptions, the signal received by the FC from the n-th sensor at the k-th interval can be represented as

$$y_n(k) = \sqrt{E_{\text{TH}}} \cdot x_n(k) + v_n(k) \tag{3}$$

where $v_n(k)$ is the additive white Gaussian noise (AWGN) with single-sided power spectral density N_0. The model in (3) assumes an AWGN channel, and the analysis in this paper can be extended to systems with flat fading channels.

Based on the model in (3), define the average impulse density of the n-th sensor node over a duration of KT_s as

$$V_n = \frac{\sum_{k=1}^K x_n(k)}{KT_s}. \tag{4}$$

With the proposed IHSC scheme, the impulse density is proportional to the vibration intensity of the monitored structure, thus it can be used as an important indicator of the health condition of the structure.

III. Optimum Impulse Density Estimation in a One-Node System

In this section we present an optimum receiver for the estimation of the impulse density, V_n, in a one-node system employing the IHSC scheme. The results will be used as a foundation for the development of optimum receivers for multi-node systems.

A. Iterative Impulse Density Estimation

In order to obtain an estimate of the impulse density V_n, we need to find the values of $x_n(k)$, for $k = 1, \cdots, K$. The value of $x_n(k)$ can be detected with the optimum MAP detection criterion, as

$$\hat{x}_n(k) = \underset{b \in \mathcal{B}}{\text{argmax}}\ p(y_n(k)|x_n(k) = b)P(x_n(k) = b) \tag{5}$$

where $\mathcal{B} = \{0, 1\}$, and $p(y_n(k)|x_n(k) = b) = \frac{1}{\sqrt{\pi N_0}} \exp\left\{-\frac{1}{N_0}\left[y_n(k) - \sqrt{E_{\text{TH}}}b\right]^2\right\}$.

After some algebraic manipulations, the decision rule in (5) can be alternatively represented as $\hat{x}_n(k) = 1$, if $y_n(k) \geq \lambda$, and $\hat{x}_n(k) = 0$ otherwise, where the threshold λ is

$$\lambda = \frac{\sqrt{E_{\text{TH}}} + N_0 \ln\left(\frac{1-\gamma}{\gamma}\right)}{2\sqrt{E_{\text{TH}}}}. \tag{6}$$

with $\gamma = P(x_n(k) = 1)$ as defined in (1).

The optimum MAP detection described in (5) and (6) requires the knowledge of the parameter, γ, which is not available at the receiver. To solve this problem, we propose an iterative method for the joint estimation of γ and $x_n(k)$.

At the beginning of the iteration, the initial value of γ is set as $\gamma^{(0)} = 0.5$. During the i-th iteration, we apply $\gamma^{(i-1)}$ from the $(i-1)$-th iteration in (5), and get the estimates $\hat{x}_n^{(i)}(k)$, for $k = 1, \cdots, K$, with the superscript representing the number of iterations. The estimated values are then used to obtain an estimate of $\gamma^{(i)}$ as

$$\hat{\gamma}^{(i)} = \frac{1}{K}\sum_{k=1}^K \hat{x}_n^{(i)}(k) \tag{7}$$

The iteration will be terminated if $|\hat{\gamma}^{(i)} - \hat{\gamma}^{(i-1)}| < \epsilon$, with ϵ a predefined threshold value, or the maximum number of iterations is reached. Once terminated, we can get an estimate of the vibration density as $\hat{V}_n = \frac{\hat{\gamma}}{T_s}$.

Simulation results demonstrate that the proposed iteration method usually converges after less than 5 iterations.

B. Performance Analysis

The theoretical expression of the estimation MSE, $\sigma_n^2 = \mathbb{E}\left(|V_n - \hat{V}_n|^2\right)$, of the proposed impulse density estimation algorithm is derived in this subsection.

To facilitate analysis, define $U_n = \sum_{k=1}^{K} x_n(k)$, and $\hat{U}_n = \sum_{k=1}^{K} \hat{x}_n(k)$. Then both U_n and $\hat{U}_n$ are binomial RVs, *i.e.*, $U_n \sim B(K, \gamma)$, and $U_n \sim B(K, \hat{\gamma})$, with $\hat{\gamma} \triangleq P(\hat{x}_n(k) = 1)$. The MSE can be written as $\sigma_n^2 = \frac{1}{(KT_s)^2}\mathbb{E}\left(|U_n - \hat{U}_n|^2\right)$. We have the following Lemma regarding the probability $\hat{\gamma}$.

Lemma 1: The probability $\hat{\gamma}$ can be calculated as

$$\hat{\gamma} = (1-\gamma)Q\left(\frac{\lambda}{\sqrt{N_0/2}}\right) + \gamma Q\left(\frac{\lambda - 1}{\sqrt{N_0/2}}\right), \tag{8}$$

where $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} \exp\left(-\frac{u^2}{2}\right) du$ is the Gaussian-Q function, and λ is defined in (6).

Proof: The probability $\hat{\gamma}$ can be expressed as $\hat{\gamma} = P(\hat{x}_n(k) = 1|x_n(k) = 0)(1-\gamma) + P(\hat{x}_n(k) = 1|x_n(k) = 1)\gamma$. Based on the MAP decision rule in (5) and (6), we have $P(\hat{x}_n(k) = 1|x_n(k) = 0) = Q\left(\frac{\lambda}{\sqrt{N_0/2}}\right)$, and $P(\hat{x}_n(k) = 1|x_n(k) = 1) = Q\left(\frac{\lambda-1}{\sqrt{N_0/2}}\right)$. Combining the above equations leads to (8). ■

With Lemma 1, we can derive the exact MSE expression for the estimation algorithm, and the results are presented in the following Proposition.

Proposition 1: The MSE of the impulse density estimated with the optimum MAP detection for a one-node system is

$$\sigma_n^2 = \frac{1}{KT_s^2}\left[(K-1)(\gamma - \hat{\gamma})^2 + \gamma + \hat{\gamma} - 2\gamma Q\left(\frac{\lambda - 1}{\sqrt{N_0/2}}\right)\right]. \tag{9}$$

Proof: The MSE can be expanded as $\sigma_n^2 = \frac{1}{(KT_s)^2}\left[\mathbb{E}(U_n^2) - 2\mathbb{E}(U_n\hat{U}_n) + \mathbb{E}(\hat{U}_n^2)\right]$. Since U_n and $\hat{U}_n$ are binomial distributed, we have $\mathbb{E}(U_n^2) = K\gamma(K\gamma - \gamma + 1)$, and $\mathbb{E}(\hat{U}_n^2) = K\hat{\gamma}(K\hat{\gamma} - \hat{\gamma} + 1)$.

Based on the definition of U_n and $\hat{U}_n$, we have

$$\mathbb{E}(U_n\hat{U}_n) = \sum_{j \neq k} \gamma\hat{\gamma} + \sum_{j=k} \mathbb{E}[x_n(k)\hat{x}_n(k)]. \tag{10}$$

The second term in (10) can be expressed as $P(\hat{x}_n(k) = 1|x_n(k) = 1)P(x_n(k) = 1) = \gamma Q\left(\frac{\lambda-1}{\sqrt{N_0/2}}\right)$. Combining the above equations leads to (9). ■

IV. Optimum Impulse Density Estimation in a Multi-Node System

The optimum impulse density estimation in a multi-node system is discussed in this section. In a multi-node system, the estimation accuracy can be further improved by exploiting the spatial sensor correlation.

A. Iterative Impulse Density Estimation

To utilize the spatial data correlation, we will jointly estimate the data from all the nodes, $\mathbf{x}(k) = [x_1(k), \cdots, x_N(k)]^T \in \mathcal{B}^{N\times 1}$, based on the received signal vector, $\mathbf{y}(k) = [y_1(k), \cdots, y_N(k)]^T \in \mathcal{R}^{N\times 1}$, where $(\cdot)^T$ represents transpose, and $\mathcal{R}$ is the set of real numbers. At the detection interval k, the joint MAP detection of $\mathbf{x}(k)$ is

$$\hat{\mathbf{x}}(k) = \underset{\mathbf{b}\in\mathcal{B}^N}{\text{argmax}}\ p(\mathbf{y}(k)|\mathbf{x}(k) = \mathbf{b})P(\mathbf{x}(k) = \mathbf{b}), \tag{11}$$

where $p(\mathbf{y}(k)|\mathbf{x}(k) = \mathbf{b})$ takes the form of a multi-variant Gaussian probability density function (pdf) with the mean vector $\mathbf{b}$ and the covariance matrix $\frac{N_0}{2}\mathbf{I}_N$, with $\mathbf{I}_N$ being a size-N identity matrix.

The MAP detection rule described in (11) requires the knowledge of $\gamma_{\mathbf{b}} \triangleq P(\mathbf{x}(k) = \mathbf{b})$, which is unknown at the receiver. Following a similar approach as the one-node case, we propose to perform joint estimation of $\gamma_{\mathbf{b}}$ and $\mathbf{x}(k)$ with an iterative method.

At the beginning of the iteration, it is assumed that the data from all the nodes are uncorrelated, and the initial value of the *a priori* probability is $\gamma_{\mathbf{b}}^{(0)} = 0.5^N$. During the i-th iteration, we apply $\gamma_{\mathbf{b}}^{(i-1)}$ from the $(i-1)$-th iteration in (11), and get the estimates $\hat{\mathbf{x}}^{(i)}(k)$, for $k = 1, \cdots, K$. The estimated values are then used to obtain an estimate of $\gamma_{\mathbf{b}}$ as

$$\gamma_{\mathbf{b}}^{(i)} = \frac{1}{K}\sum_{k=1}^{K} I(\tilde{\mathbf{x}}^{(i)} - \mathbf{b}), \quad \forall \mathbf{b} \in \mathcal{B}^{N\times 1} \tag{12}$$

where the indicator function $I(\mathbf{0}) = 1$, and $I(\mathbf{x}) = 0$ if $\mathbf{x} \neq 0$. It should be noted that the estimation of the *a priori* probability in (12) implicitly takes into consideration of the mutual correlation among the data in $\mathbf{x}(k)$.

The iteration will be terminated if $\max_{\mathbf{b}}\{\gamma_{\mathbf{b}}^{(i)} - \gamma_{\mathbf{b}}^{(i-1)}\} < \epsilon$, or the number of iterations exceeds a predefined threshold. At the end of the iteration, we can get an estimate of the impulse density of the n-th node as

$$\hat{V}_n = \frac{1}{KT_s}\sum_{k=1}^{K} \hat{x}_n(k). \tag{13}$$

The optimum MAP detection requires the exhaustive search of the space $\mathcal{B}^N$, and the complexity grows exponentially with the node number, N. A sub-optimum spatial MAP detection method is presented in Section V to balance the tradeoff between the complexity and performance.

B. Performance Analysis

The exact MSE of the optimally estimated impulse density in a multi-node system is presented in this section.

Proposition 2: For a multi-node system that employs the optimum MAP detection, the MSE of the estimated impulse density at each sensor location can be calculated by

$$\sigma_n^2 = \frac{1}{KT_s^2}\left\{(K-1)[\gamma - \hat{\gamma}_N(\theta)]^2 + \gamma + \hat{\gamma}_N(\theta) - 2\alpha_N(\theta)\right\} \tag{14}$$

where $\hat{\gamma}_N(\theta) = P(\hat{x}_n(k) = 1|N, \theta)$ is the conditional probability of detecting 1 when there are N nodes with a spatial correlation coefficient θ, and $\alpha_N(\theta) = \mathbb{E}[x_n(k)\hat{x}_n(k)|N, \theta]$.

Proof: The procedure is similar to the proof of Proposition 1, and details are omitted here for brevity. ■

In (14), the impacts of the spatial node correlation are represented in the parameters $\hat{\gamma}_N(\theta)$ and $\alpha_N(\theta)$. The calculations of $\hat{\gamma}_N(\theta)$ and $\alpha_N(\theta)$ are quite tedious. Here we only present the values of $\hat{\gamma}_2(\theta)$ and $\alpha_2(\theta)$ in a two-node system as follows

$$\hat{\gamma}_2(\theta) = (1-2\gamma+\rho)(b_2^2 + b_1\bar{b}_2 - s_{00}) + \rho(a_2^2 + a_1\bar{a}_2 - s_{11}) + (\gamma-\rho)(2a_2b_2 + \bar{a}_2b_1 + a_1\bar{b}_2 - s_{01} - s_{10})$$

$$\alpha_2(\theta) = (\gamma-\rho)(\bar{b}_2a_1 + b_2a_2 - s_{10}) + \rho(\bar{a}_2a_1 + a_2^2 - s_{11})$$

where $\rho = \theta\sigma_1\sigma_2$, $a_i = Q(\frac{\lambda_i - 1}{\sqrt{N_0/2}})$, $\bar{a}_i = 1 - a_i$, $b_i = Q(\frac{\lambda_i}{\sqrt{N_0/2}})$, $\bar{b}_i = 1 - b_i$, and

$$s_{ij} = \int_{\lambda_2}^{\lambda_1} \frac{1}{\sqrt{\pi N_0}} e^{-\frac{(y_1-i)^2}{N_0}} \left[Q\left(\frac{\lambda_2 - j}{\sqrt{N_0/2}}\right) - Q\left(\frac{w}{\sqrt{N_0/2}}\right)\right] dy_1,$$

with $w = \lambda_1 + \lambda_2 - y_1 - j$, $\lambda_1 = \frac{\sqrt{E_{\text{TH}}} + N_0 \ln\left(\frac{1-2\gamma+\rho}{\gamma-\rho}\right)}{2\sqrt{E_{\text{TH}}}}$, $\lambda_2 = \frac{\sqrt{E_{\text{TH}}} - N_0 \ln\left(\frac{\rho}{\gamma-\rho}\right)}{2\sqrt{E_{\text{TH}}}}$, and $i, j = 0, 1$. The derivation of the above result is omitted here for brevity.

V. Iterative multi-node Estimation with Sub-optimum Spatial MAP Detection

A sub-optimum spatial MAP impulse detection method is presented in this section to achieve a tradeoff between the computation complexity and performance.

The spatial MAP algorithm reduces the computation complexity by performing the impulse detection for each node individually with the MAP criterion, as against the joint MAP detection in the optimum algorithm as described in (11). To utilize the spatial correlation among the nodes in the sub-optimum algorithm, the *a priori* probability that is necessary in the MAP detection is calculated by collecting the information from all the nodes in the spatial domain.

At the detection interval k, the MAP detection of $x_n(k)$ from the n-th node can be described as (c.f. (6))

$$\lambda_k = \frac{\sqrt{E_{\text{TH}}} + N_0 \ln\left(\frac{1-\gamma_k}{\gamma_k}\right)}{2\sqrt{E_{\text{TH}}}}, \tag{15}$$

with $\gamma_k = P(x_n(k) = 1)$. It should be noted that, in the sub-optimum algorithm, it is assumed that the *a priori* probability, γ_k, and the detection threshold, γ_k, are functions of the time index, k.

The MAP algorithm described in (15) requires the knowledge of the *a priori* probability, γ_k. We propose to estimate γ_k by utilizing information from all the nodes in the spatial domain. Define the spatial average of the transmitted signals and the received signals as $\Delta(\mathbf{x}(k)) = \frac{1}{N}\sum_{n=1}^N x_n(k)$ and $\Delta(\mathbf{y}(k)) = \frac{1}{N}\sum_{n=1}^N y_n(k)$, respectively. Based on the strong law of large numbers, we have

$$\lim_{N\to\infty} \Delta(\mathbf{y}(k)) = \lim_{N\to\infty} \Delta(\mathbf{x}(k)) = \sqrt{E_{\text{TH}}} \cdot \gamma_k. \tag{16}$$

Therefore, when the number of nodes, N, is large, we can get an estimate of γ_k as

$$\hat{\gamma}_k = \frac{\Delta(\mathbf{y}(k))}{\sqrt{E_{\text{TH}}}}. \tag{17}$$

The spatial MAP operation described in (15) and (17) has a complexity in the order of $\mathcal{O}(N)$, which is significantly lower compared to the joint MAP detection with a complexity in the order of $\mathcal{O}(2^N)$, especially when N is large.

VI. Simulation Results

Simulation results are presented in this section to verify the performance of the proposed ULP IHSC scheme and the optimum and sub-optimum impulse density estimation algorithms.

In the simulation, it is assumed that the mean, μ, of the exponentially distributed energy harvesting time is 1 s. The detection duration is $T_s = 10$ ms. The correlated Bernoulli RVs, $x_n(k)$, are generated by using the method described in [9]. The iterative impulse density detection is performed over 100 s, which corresponds to $K = 10^4$ detection intervals. The average SNR is calculated as $\nu = \frac{E_{\text{TH}}T_s}{N_0\mu}$. Unless otherwise stated, the receiver does not have any *a priori* knowledge of the probability, $P(\mathbf{x}(k))$, or spatial correlation coefficient, θ.

Fig. 1 shows the MSE of the estimated impulse density for a one-node and a two-node system with the optimum MAP detection at the FC. The simulation results obtained from systems with both known and unknown *a priori* probability at the receiver are plotted in the figure for comparison. The spatial correlation coefficient of the two-node system is $\theta = 0.9$. We have the following observations of the results. First, the system can operate at extremely low SNR due to the low duty cycle and the innovative IHSC scheme. When SNR = -6 dB, an MSE of 3×10^{-5} and 1×10^{-5} is achieved by the one-node system and two-node system, respectively. Second, when SNR > -8 dB, the iterative estimation methods with unknown *a priori* probability can achieve a performance that is identical to that of a system with known *a priori* probability. This demonstrates the effectiveness of the proposed iterative estimation method. Third, the analytical results match very well with the simulation results when SNR > -8 dB. Fourth, at MSE = 10^{-4}, the two-node system outperforms the one-node system by 1.2 dB. The performance improvement is contributed by the utilization of the spatial node correlation.

The impact of the spatial correlation coefficient, θ, on the MSE performance is shown in Fig. 2 for a two-node system. As expected, the MSE performance improves consistently as θ increases. When MSE = 10^{-5}, the system with $\theta = 1$ outperforms that with $\theta = 0.5$ by 2.8 dB. The results demonstrate that the proposed algorithm can effectively utilize the spatial correlation between the nodes.

Fig. 3 compares the MSE performance between the optimum joint MAP detection and the sub-optimum spatial MAP detection. The spatial correlation coefficient is $\theta = 0.9$. For both the optimum and sub-optimum algorithms, the MSE performance improves consistently as N increases. This demonstrates that the sub-optimum algorithm can effectively utilize the spatial correlation among sensors. As expected, the optimum algorithm outperforms the sub-optimum algorithm under all the system configurations. When $N = 10$ and MSE = 10^{-5}, the sub-optimum algorithm is 1.1 dB away from the optimum algorithm. The 10-node system with the MAP detection can achieve an MSE of 5×10^{-5} at SNR = -8 dB.

VII. Conclusions

A new paradigm of integrated harvesting, sensing, and communication scheme was proposed for ULP SHM. The IHSC scheme was designed by exploiting the correlation between the harvested energy and vibration intensity. The structure vibration information is carried as the densities of the impulses generated by the sensors. Impulse density estimation algorithms based on the optimum joint MAP detection and sub-optimum spatial MAP detection were proposed, and exact analytical expressions were derived for the optimum algorithms. The simulation and analytical results indicated the both the optimum and sub-optimum estimation algorithms can take advantage of the spatial correlations among the sensors, and the system can operate effectively at the ULP regime without battery or external energy sources.

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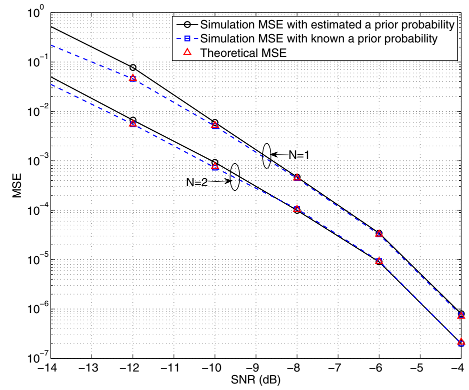

Fig. 1. MSE for systems with optimum impulse density estimation.

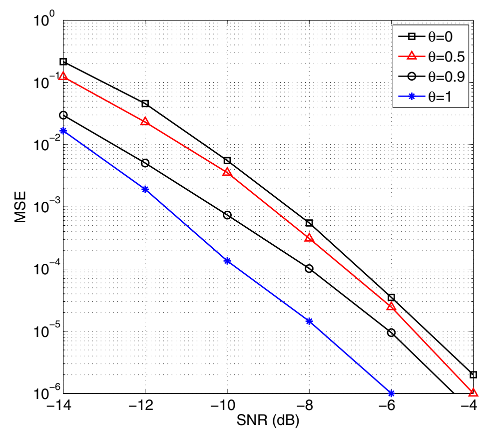

Fig. 2. Impulse density MSE with different values of spatial correlation coefficient, θ.

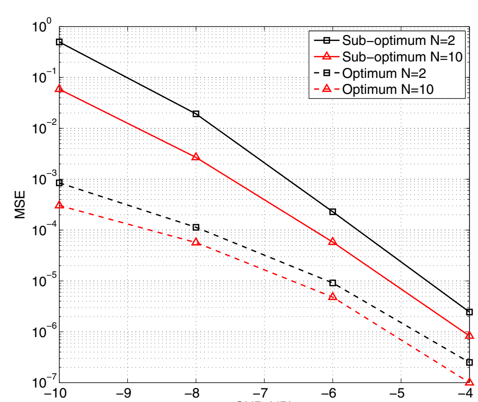

Fig. 3. Comparison of the optimum and sub-optimum estimation algorithms.