Small Battery-Free Wireless Sensor Networks for Structural Health Monitoring

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ABSTRACT[1]

Battery-free wireless sensors developed at the University of Maine under a cooperative agreement with NASA enable a myriad of structural health monitoring (SHM) applications. Embedding these sensors in structures without the need for changing batteries, their rugged design to withstand harsh environments, and coded communication with multiple access features makes this new technology a desirable candidate for a variety of aerospace and civil infrastructure monitoring applications. This paper presents sensor characteristics, communication schemes, and multi tier networking strategies developed to deliver a reliable wireless sensor system for SHM. A large scale inflatable lunar habitat structure built by NASA and instrumented by UMaine is used as test-bed for technology demonstration. Various aspects of this system have been studied and results are published in conferences and journals as presented in the references section. These aspects are summarized in this paper and include: distributed sensing and coding, throughput optimization, channel estimation error analysis, signal detection in presence of interference, two-tiered networking, turbo coding and decoding in distributed sensor networks, cooperative relaying methods, and impact localization. Testing the developed battery free sensors in lab environment with multi-path and interference effects resulted in 16 ft operation range with under 20 mW power. This range can be even extended further if a second tier with battery-operated sensors is added to the network. Noting that several passive sensors and only a few active sensors is required to build this multi-tier architecture, the cost savings in power combined with coding gain is significant compared to conventional sensor networks.

INTRODUCTION

One of the major problems in practical use of wireless sensor networks (WSN) is power consumption. Numerous research and development works have been devoted to reduce power consumption through efficient power management strategies at physical, network, and upper layers [1-6]. Considerable efforts have been invested

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toward lowering the power consumption by improving sensor network platforms, including selectable power states (off, sleep, standby), operating at low voltages, fine grained control of hardware, and efficient use of wireless broadcast medium [1]. Modulation scaling is used for energy aware wireless packet scheduling to meet the low power requirement [2]. Randomizing the choice of both measurement and transmit rate is proposed in [3] to optimize detection performance with certain power constraint in time-varying noisy environments. Properties of sensor data is exploited in [4] to eliminate overhead on the sensor nodes and therefore save the energy consumed by WSN. Furthermore, numerous researches have been conducted on the optimization of protocol stack for the design of networks to achieve longer lifetimes for the systems [5]. A protocol architecture is developed for WSN called Low-Energy Adaptive Clustering Hierarchy (LEACH), which includes a distributed cluster formation technique for self-organization. This protocol is energy efficient since it uses hierarchy to reduce the data collected before transmission to the cluster head. A Physical (PHY) layer driven approach is proposed in [6] to design protocols and algorithms that minimize the energy consumption of the WSN and individual nodes, where energy per useful bit required to decode different rate convolutional codes with varying constraint lengths are measured.

These elegant solutions work fine in specific applications with short term deployment or access to wireless sensor nodes for battery replacement, while they fall short in long term deployments especially when sensors are embedded in structures or machines in hard to reach areas making the battery replacement impossible or very costly. In addition, usage of wireless sensors in ***harsh environments*** with extremely hot or cold temperatures is also limited due to battery/device limitations. Solutions proposed in the literature advanced the area via increasing temperature tolerance for both batteries and electronic circuits to about 400ºC [7]. These impediments reveal the important role of ***Battery-less or Passive*** wireless sensors to enable practical applications in extreme conditions. Battery-less sensors can respond to several of these demanding applications by providing a number of important features: no battery, small size, low cost for high volume production, and capability to withstand harsh environments, such as on moving parts at high temperatures or pressures, or in the presence of hazardous chemicals [8].

A battery-less sensor consists of metal electrodes photo-lithographically printed onto a piezoelectric crystalline substrate. These electrodes can be used to implement matched filter transfer functions, which allow the identification of each individual sensor. This capability leads to new wireless and passive sensor applications in which multiple sensors in close proximity must be individually interrogated. These sensors can be designed to operate on crystals such as lithium niobate (LNO). Transducers need to be phase-coded based on design criteria established for matched filters used in correlation receivers [9]. The coded transducers are designed to respond to the coded sequences to which they are matched, allowing sensors to be addressed individually. The sensor output is the differential delay between the responses of the two coded transducers. The delay of each path is dependent on the wave propagation velocity on the substrate. The device can be used for physical sensing, because this velocity can be affected by variations in temperature, pressure, vibration, and mass loading. By depositing a thin film on one of the delay paths, sensitive and selective to a specific chemical or biological compound, the sensor can detect that particular measurand.

One major practical challenge in designing battery-less sensors is orthogonal code design for sensor network applications. Quasi-orthogonal codes are required to be designed and implemented on the miniaturized wireless differential-delay sensor. The main objective of orthogonal code design is to add multiple access features to passive sensors. The proposed codes are selected based on their auto-correlation and cross-correlation characteristics. The following criteria are used to select the most appropriate codes for this application:

i. Largest peak-to-side lobe ratio of the auto-correlation response of a given code
ii. Smallest maximum peak value of cross-correlation of that code with any other code in the set

Depending on the thresholds for the two criteria, one could generate larger or smaller final subsets of codes. The proposed scheme in this chapter is different from the methods based on finite projective planes [10], where only auto-correlation is minimized. The proposed code design method is developed based on the experimental results with battery-less sensor devices, where imperfection in the device fabrication process leads to undesired side lobes in the sensor response. As an example, a set of 31 codes has been designed in [11]. The process starts with a set of 1024 codes which is later reduced to a subset with a peak to side lobe ratio (of their auto-correlation) of 5 or greater. This drops the subset size down to 73 codes.

HYBRID SENSOR NETWORKS

Networking passive (battery-less) and active (battery operated) sensor nodes fully exploits the cross layer approach benefits by achieving goals of embedded sensors applications while, providing the added range and advantages of active sensors.

Estimation of a parameter in an inaccessible area using multiple observations, the so called Chief Executive Officer (CEO) problem, is still a challenging problem in the WSN [12]. This problem can be addressed using distributed coding scheme implemented in a hybrid sensor network with double-sink configuration. Noting the high correlation among sensors' observations, the overall data flow efficiency of the system can be considerably improved using Distributed Source Coding (DSC) techniques based on the Slepian-Wolf theorem [13]. The sensor node can be simplified by combining distributed source and channel coding into a Distributed Joint Source Channel Coding (D-JSCC), without degradation in BER performance [14].

Most reported D-JSCC schemes in the literature are still too complex for the computationally constrained sensors [15]. A practical low complexity DJSCC solution is introduced in [16] based on Recursive Systematic Convolutional Codes (RSC) equipped sensors that form a distributed version of Parallel Concatenated Convolutional Codes (PCCC). The proposed iterative decoding algorithm with self-correlation extraction property may be employed in a double-sink two-tiered WSN. In a traditional clustered two-tiered WSN structure, a sink node collects data from sensors inside a cluster and relays it to the data fusion center located at a base station using different relaying modes [17]. A new system model is proposed in [18] in which two sink nodes are placed at each cluster. DeModulate and Forward (DMF) relaying mode is applied to sink nodes, since it enables the sink nodes to reformat the frames into a multi-frame and forward it to the base station. This is not applicable to the widely used Amplify and Forward (AF) relaying mode.

The links from each sensor to the base station form a two-hop multi-relay communication system. It is shown that for a multi-relay system which employs Distributed Space-Time Block Codes (D-STBC) assisted AF relaying mode, the optimum power allocation between source and relay nodes, is equal power allocation [19]. BER performance for these systems with equal power allocation is analyzed in [20].

DISTRIBUTED SOURCE ESTIMATION

The structure depicted in Fig. 1 includes two tiers which require a cross layer approach for its design. First tier of the system is composed of clusters of sensors. Each cluster includes a binary source observed by a group of sensors. The source data of different clusters assumed to be uncorrelated. There is no overlap between clusters, and each sensor belongs to a unique cluster. Hence, we focus on one cluster in this chapter. The channels from sensors to the sink nodes are orthogonal either in time or frequency. Both sinks listen to the same channel set and receive different versions of the same signal. The second tier is composed of two sink nodes per cluster that forward the received signals from sensors to the base station using a method explained later in this section. All channel coefficients are assumed to be independent zero-mean complex Gaussian random variables.

The optimum power allocation for DMF relaying mode is calculated in [18] and an upper bound on the system BER performance as a function of sensor's observation accuracy, number of sensors, and end to end system SNR value is derived.

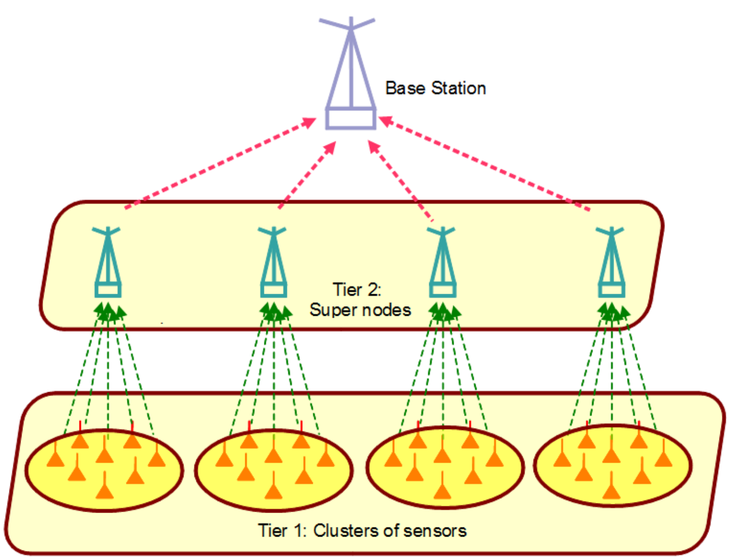

Figure 1. System model for two-tiered double-sink wireless sensor network.

$$p_e < \sum_{i=\left\lfloor \frac{M}{2} \right\rfloor + 1}^{M} \binom{M}{i} p^i q^{M-i} + \frac{(-1)^M + 1}{4} \binom{M}{\frac{M}{2}} (pq)^{\frac{M}{2}} \tag{1}$$

where $p = q - 1$ and the error probability between tier 1 and 2 for signal to noise ratio of γ_1 and γ_2 is

$$p = \frac{1}{4(\gamma_1 + 1)} + \frac{1}{2(\gamma_2 + 2)^2} - \frac{1}{4(\gamma_1 + 1)(\gamma_2 + 2)^2} \tag{2}$$

Fig. 2 presents the impact of power allocation on inner channel error probability. Despite the case of Space Time Block Coded (STBC) assisted Amplify and Forward (AF) relaying, which has been proven to yield optimum performance for equal power allocation among sensors (source) and sinks (relay), the performance curve for DMF relaying mode is not symmetric. Dashed and solid lines in this figure presents analytical and simulation results of error probability as a function of power allocation parameter.

Simulation results verify the analytical expression, specially for large SNR values, where the approximations are held better. One interesting result is that allocating more power to the sensor nodes, specially at large SNR values improves the performance. The optimum power allocation scenario can be chosen based on the average SNR value of the system. The optimum power allocation parameters for some SNR values are marked in this figure. This result provides a new criterion to configure clustered WSN for CEO applications to achieve a desired performance with minimum number of sensors in a cross layer approach in hybrid wireless sensor networks.

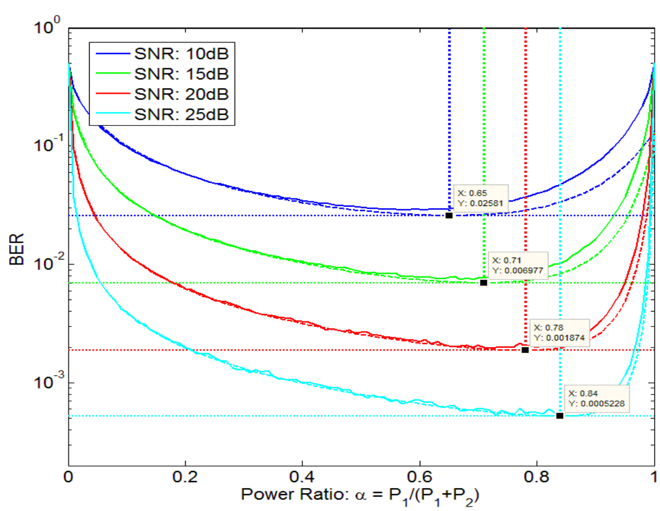

Figure 2. Probability of error for inner channels versus power allocation parameter.

IMPACT LOCALIZATION

A challenging aspect of impact detection is accurate localization of the impact over the structure's surface. Similar problems have been explored for years, ranging in application from radar detection of aircraft in an airport, to the position of a receiver using Global Positioning System (GPS). In this respect, the fundamentals of detecting an object's location is well researched and commonly known, however, its implementation requirements can change drastically from one environment to another. In this section, a hybrid time of arrival and amplitude based impact localization is presented as an example application using sensors in proximity of a source for precise source estimation.

The test-bed used for the experimental verification of this theory is illustrated in Fig. 3. This large scale inflatable lunar habitat structure built by NASA and instrumented by UMaine is used as test-bed for technology demonstration. UMaine's students installed accelerometer sensors and designed data acquisition and analysis hardware and software for impact localization. Once the structure is hit by a precise impact hammer, each sensor experiences different signal intensities at different times. Typical sensor responses in X-Y-Z directions are depicted in Fig. 4. These responses are then analyzed using the algorithm detailed in [21] to produce precise location estimates as presented in Fig. 5.

By characterizing the environment to modify the Friis equation, one can make reasonable projections of the power received at an antenna at a given distance. Having this information, the transmitted power, and the received power, a distance from the transmitter can be calculated. By having more than one receiver, the system can determine the location of the transmitter via trilateration.

Figure-3: Inflatable lunar habitat test-bed at UMaine with 42 ft diameter is 10 ft high.

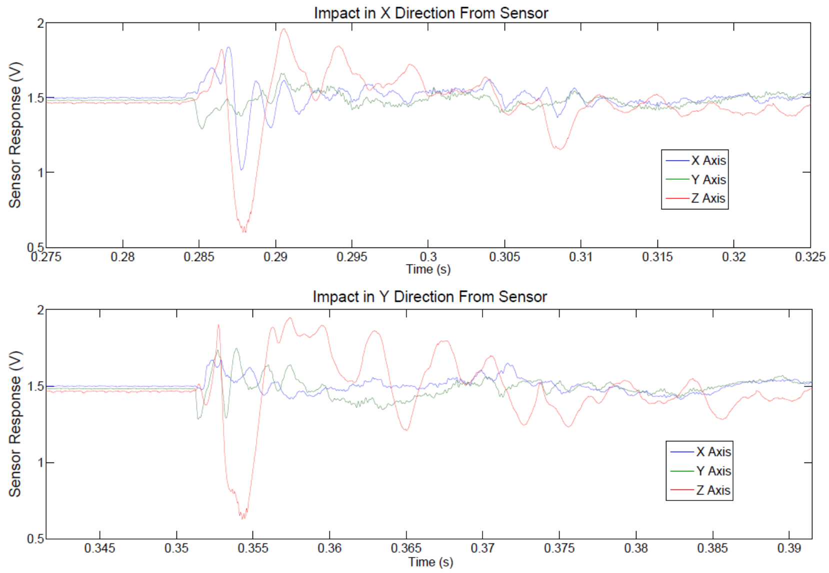

Figure-4: Sensor responses from impacts.

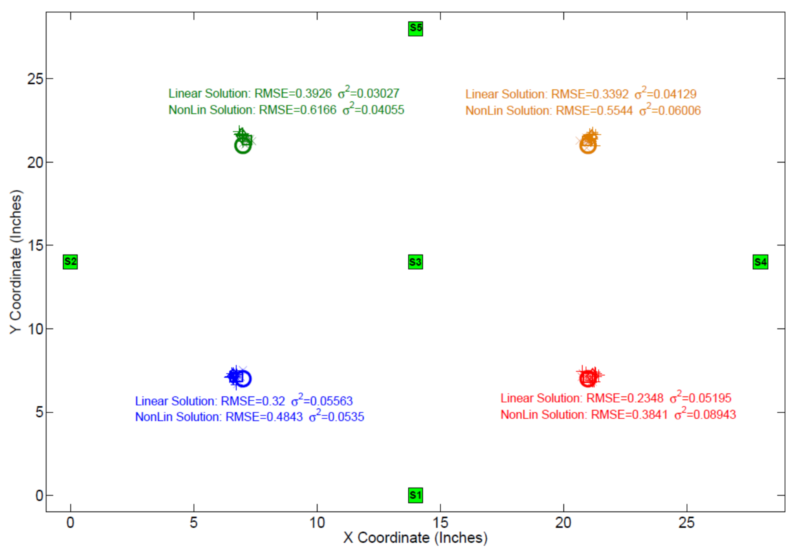

Figure-5: Localization of impacts using hybrid time of arrival and amplitude.

CONCLUSIONS

Code design process for passive wireless sensors is developed to provide multiple access and high isolation among several sensor nodes. Furthermore, system information capacity is derived as a function of observation accuracy, channel quality and the number of sensors. The derived expression for the capacity defines the achievable capacity for different number of sensors. A practical distributed coding scheme is also proposed that provides acceptable performance using the intrinsic correlation among sensors data. Impact localization was studied as a special application case. Algorithms were developed for accelerometer based impact localization, and impact scaling.

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