Bandwidth constrained distributed estimation for wireless sensor networks

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Abstract. The focus of this paper is power constrained in wireless sensor networks. We purpose an adaptive transmit power levels based on sensors noise variance and channel conditions. We also investigate its impact on energy saving. First, the measurement results of the sensors are quantized into discrete messages. Second, the quantized data are transmitted to the fusion center where a final estimate is generated. The optimal transmit power levels for each sensor is determined by the sensor noise levels and channels conditions from sensor to the fusion center. The goal is minimized the total transmitting power, while ensuring a given Mean Squared Error (MSE) performance. The sensor will be active when the measurement results of the sensors have low noises variances and the condition of the channel between the sensor and the FC is good and if the conditions are otherwise the sensor is not active with the aim of saving power. For the remaining active sensors, their optimal transmit power levels are determined jointly by individual channels gain, local observation noise variance sensor and the targeted MSE performance. Numerical examples show that an adaptive power levels achieves significantly smaller MSE than uniform power levels for the same average power consumption.

1. Introduction

A wireless sensor network is a network that consists of a number of sensors deployed in the certain areas, which are called the field of sensors. The main task of WSN is to detect natural phenomena such as temperature, humidity, pressure, movement of vehicles, and others. The sensor consists of three components, sensing, processing data and communication devices. The development of digital and wireless communication technologies makes it possible to produce many sensors, which are small sized, multi-function, low power and be able to communicate over short distances [1].

Recently the wireless sensor network (WSN) technology has developed rapidly because these is the one of the solutions to challenging problem in various fields such as environmental, military, health, home, and other commercial applications. However, the main challenge in the implementation of WSN is the limitation of energy and bandwidth of communication because the sensor is powered by battery, which has a limited lifetime [2-5].

A common Wireless Sensor Networks (WSN) architecture consists of a fusion center and a number of geographically distributed sensors. In this paper consider decentralized estimation of unknown parameter by a set of distributed sensor nodes and fusion center. The problem of decentralized estimation has been extensively studied, first in context of distributed control, later in tracking and data fusion [6]. Most of this works assume that the joint distribution of sensor observations is known and the real messages can be sent from sensor to the fusion center without distortion. These assumptions are
unrealistic for practical sensor networks since the wireless links between the sensors and the fusion center invariably suffer from adverse channels effects such as attenuation and fading.

This paper considers the model of the wireless link between sensor and fusion center as additive white Gaussian noise (AWGN) channels under suitable channels path loss. To minimize the total energy consumption, each sensor optimally chooses the number of quantization levels and transmitting power levels by taking into account both their local SNRs and individual channel path losses.

This paper is organized as follow: section II methods. The design of optimal quantization scheme for each sensor based on their SNRs and channels path loss described in Section III. The numerical analysis is presented in section IV and finally concluding remark are given in Section V.

2. Methods
The system in this study is a WSN with a star topology, one hop, where a set of sensors takes measurements and sends quantified measurement results to a data processing center or fusion center (FC). However, the results of this study can be used for other topologies and multi hops. The system image used is shown in Figure 1. Consider a set of $K$ distributed sensors, each making an observation on a random signal estimated $\theta$. The observations are corrupted by additive noises and are described by Luo [7]:

$$x_k = \theta + n_k, \quad k = 1, \ldots, K$$

The noise $n_k : k = 1,2,\ldots, K$ are zero mean spatially uncorrelated with variance $\sigma_k$, but otherwise unknown. Each sensor performs a local quantization of $x_k$ and generates a quantization message $m_k(x_k, L_k)$ of $L_k$ bits. Each message is then transmitted to the FC through a separate AWGN channels with a known path loss coefficient, and the FC generates the final estimate of $\theta$ based on the received signals. In this paper use the Mean Squared Error (MSE) criterion to measure the quality of an estimator for $\theta$.

![figure1](http://example.com/figure1.png)

**Figure 1.** Decentralized estimation with adaptive quantization.

2.1. Power allocation
Each sensor locally quantizes the analog observations $x_k$ into discrete message $m_k(x_k)$, of length $L_k$ bits. These local estimates are transmitted to FC. The channel between sensor and FC is corrupted with additive white Gaussian noise (AWGN). The channels are assumed to be loss and the path loss is given by $a_k = d_k^\alpha$, where $d_k$ is the transmission distance and $\alpha$ is the path loss exponent. At the FC final estimation is performed by combining these messages.

The goal is optimally choosing quantization and transmits power levels at each sensor ($P$), while ensuring a targeted MSE performance ($D_0$). The formula of power optimization is:

$$\min \|P\|_2$$

s.t. $D' \leq D_0 \quad L_k \geq 0$$
Where $D'$ are the achieved MSE performance. $L_k$ is an integer signifying the number of quantized bits per sample at the sensor $k$.

The implement the described adaptive quantization scheme sees Fig.2. The FC broadcast the threshold $\eta_0$ whose value is based on the collected network information. Each sensor decided the quantization message length $L_k$ according to its own local information ($\sigma_k, a_k$) and $\eta_0$. The sensor with $\sigma_k \leq W$ and $a_k \leq \eta_0$ will transmit a message with length $L_k \geq 1$. $L_k$ is determined from simulation. Otherwise sensor with $\sigma_k \geq W$ and $a_k \geq \eta_0$ should be inactive to save energy consumption.

3. Results and discussion

The main task of the sensor network is to monitor the physical condition of an environment and communicate the results to other sensors or to a data processing center which is often called the Fusion Center (FC) [8-9]. Distributed estimation systems that do not require knowledge of the distribution of sensor measurements that are famous for the Universal Decentralized Estimation (UDES) system have been proven to be able to overcome the challenges of resource limitations in JSN [7]. In addition, the centralization system requires a large communication bandwidth and allows the accumulation of data in FC [10]. These results indicate that this system has very good prospects for further development. This chapter describes the initial stage of the research, namely the further evaluation of the problem of resource limitations in the distributed estimation system. The aim is to obtain estimation parameters that can be improved or extended that contribute to improving resource efficiency and improving estimation performance. The main purpose of this section is to determine the number of quantization bits and the optimal amount of transmit power if a specific MSE target is desired. Implementation of the proposed algorithm.

Figure 2 shows FC sends the channel condition threshold $\eta_0$ to all sensors. The value of this threshold is based on information collected from the network. Each sensor determines the length of the quantization bit $L_k$ based on the information it has, namely the measurement noise variant $\sigma_k$, path loss $a_k$, and the threshold condition of the channel $\eta_0$ sent by FC. Because there is no knowledge about pdf sensor noise then probabilistic quantization is used which can work for all types of pdf sensor noise and produces unbiased messages.

To strengthen the analytical result, it was simulated using following parameters. The total number of sensors $K = 100$, the range of sensor measurement $W = 1$, where $W=1$ and sensor observation noise variances to be Chi-squared distribution with degree 1. Also, the channel path loss coefficients and the distance between sensor and FC are generated by a uniform distribution $[0,10]$. Each simulation is carried out $10^6$ iterations and the results displayed are the average values of the simulation results. With the power scheduling method, a smaller number of sensors is needed to achieve the desired MSE target. The proposed power efficiency method is the optimal power distribution method where the bit length quantization and transmission power allocation are determined based on variants of measurement losses and the channel condition threshold between the sensor and FC which can achieve a better MSE compared to the uniform method where the network power is shared equally to all sensors, shown in Figure 3.
Sensor transmit power, $P_k$; Quantizer; Sensor inactive

Figure 2. The algorithm of adaptive quantization.

Figure 3. Active sensor percentage if the MSE target $P_T=500$ Watt, $K=100$, $d_k \in [1,10]$, $\sigma_k^2 \in [0,1]$.

The simulation result show that when target $D_0$ increases, more sensors will become inactive. Such inactive sensors neither perform quantization nor transmit any message to the FC in order to conserve energy. Figure 3 plots the percentage of active sensors versus some target MSE $D_0 \geq DBLUE$, where DBLUE is MSE of the centralized BLUE defined in Wardihani et al [2]. This paper compared the adaptive quantization with the uniform quantization, where each sensor quantizes their measurement into the same number of bits to achieve the same target MSE. Figure 5 shows that adaptive quantization has smaller MSE than uniform quantization.
4. Conclusion
This paper derived the optimal transmit power levels in sensor networks to minimize energy consumption while satisfying a certain distortion constraint. The optimal transmission power levels for each sensor can be determined jointly in term channels path loss and the observation noise sensor. Numerical examples show that optimal power levels achieve significantly smaller MSE than uniform transmit power levels for the same average power consumption.

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