Power Efficient Distributed Wireless Sensor Networks Using Random Sampling and Sparsity

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Abstract: In this position paper, we suggest to exploit the Random Sampling (RS) technique in a Wireless Sensor Network (WSN). Being a simple technique, this way of sampling reduces the power consumption of the sensors in a WSN. The reconstruction of the signal can be accomplished using an RS recovery technique called Iterative Method with Adaptive Thresholding and Interpolation (IMATI). This recovery algorithm has a great advantage that is the capablity of being implemented either in a centeralized or distributed manner. Moreover, the complexity of the recovery techniques are low, which results in a low-power decoding system.

1 INTRODUCTION

Wireless Sensor Networks (WSN) are extensively used for various applications such as telemedice, weather forecasting stations, seismographic systems and security systems. The main drawback of these systems is that the sensor nodes have limitted unchargable power supplies. Hence, it is esssential to design low-power sensing and recovery algorithms to be used in such systems. The main goal of this position paper is to introduce power-efficient sampling and reconstruction schemes to be used in WSNs. Our suggested sampling technique is Random Sampling (RS) (Azghani and Marvasti,) (Marvasti, 2001) which is to take a number of signal samples according to a predefined random pattern. This sampling scheme does not require to be implemented synchroneously in contrary to the conventional uniform sampling technique. The reconstruction scheme is built upon the premise of sparsity property of the underlying signal (Candes et al., 2006) (Donoho, 2006). Sparsity is a well-defined characterestic of the signals which refers to the case where most of the entries of a signal are zero in some domain such as Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), or Discrete Fourier Transform (DFT) (Candes et al., 2006) (Donoho, 2006) (Candes and Wakin, 2008). Moreover, sparsity and sparse signal processing have appreared in various other applications such as medical imaging (azghani et al., 2014), machine learning (Huang and Aviyente, 2006), channel estimation (Pakrooh et al., 2012) and radar systems (Zhang et al., 2012).

In this work, we focus on the random sampling technique as one of the efficient methods for sampling sparse signals. The examples of random sampling reconstruction schemes are Iterative Method with Adaptive Thresholding (IMAT) (Marvasti et al., 2012) and Iterative Method with Adaptive Thresholding and Interpolation (IMATI) (Azghani and Marvasti, 2013). In this paper, we would use IMATI to recover the random samples. The recovery process approaches the original signal iteration by iteration. The sparsity is promoted with the aid of a thresholding operator that is changing at each iteration from a large value to a smaller one. Due to the simplicity of this iterative procedure, the algorithm would be power efficient.

The distributed implementation of these schemes can be exploited in two different ways. One is to speed up the total recovery process with the aid of multiple parallel cores of processing systems in centralized systems. The second way is to distribute the processing burden between various nodes preventing from the outage of a node which may cause a serious problem in the networks.

The rest of the paper is organized as follows: the random sampling scheme is briefly described in Section II. Section III illustrates the IMATI recovery technique. In Section IV, the method for distributed random sampling and recovery is illustrated for two scenarios. Section V concludes the paper.

2 THE RANDOM SAMPLING SCHEME

Random sampling refers to the method of taking a number of entries of a signal randomly. In random sampling, a number of entries of a signal are taken randomly. The sampling can be conducted with the aid of an inner product with a binary mask of the same size of the signal. The binary sampling mask is usually a fixed vector or matrix constructed according to a random pattern beforehand. Since the complexity of an inner product operation is considerably low, the sampling process would be of low complexity burden, resulting in a low-power encoder. Suppose the $m \times n$ matrix $\mathbf{x}$ be the signal to be sampled., and the $m \times n$ matrix $\mathbf{M}$ be the binary random sampling mask. The randomly sampled matrix, $\mathbf{y}$, would be represented as:

$$\mathbf{y} = \mathbf{M}.*\mathbf{x} \tag{1}$$

where $.*$ indicates for the inner product operation. In a wireless network, we have a number of sensors measuring a quantity in their common media.

3 RANDOM SAMPLING RECOVERY TECHNIQUES

The random sampling recovery technique that we use is IMATI (Azghani and Marvasti, 2013) illustrated in the following algorithm.

Algorithm 1 Iterative Method with Adaptive Thresholding and Interpolation (IMATI)

input:
A random sampling binary mask $\mathbf{M} \in \mathbb{R}^{m \times n}$.
A randomly sampled vector $\mathbf{y} \in \mathbb{R}^{n}$.
The maximum number of iterations $iter_{max}$.
output:
A recovered estimate $\widehat{\mathbf{x}} \in \mathbb{R}^{n}$ of the original signal.
procedure IMATI($\mathbf{y}, \mathbf{x}$)
    $\mathbf{x}^0 \leftarrow 0$
    for k=1:$iter_{max}$ **do**
        $\mathbf{x}^{k+1} \leftarrow T^k\left(\mathbf{x}^k + \lambda_1 \mathrm{Interp}(\mathbf{y} - \mathbf{M}.*\mathbf{x}^k)\right)$
    end for
    return $\widehat{\mathbf{x}} \leftarrow \mathrm{IDT}\left(\mathbf{x}^{iter_{max}}\right)$
end procedure

The *Interp* is an interpolating operator such as sample hold or linear interpolator. At each iteration, an approximation of the sampled signal is obtained. $T^k(.)$ is the thresholding operator which promotes the sparsity of the signal. The threshold value is changing with the iteration number, k, as:

$$T^k(\mathbf{x}) = \begin{cases} 0 & \text{if} \quad |x| \leq \theta(k) \\ x & \text{if} \quad |x| \geq \theta(k) \end{cases} \tag{2}$$

The DT and IDT operators are Discrete Transform (such as DCT) and its inverse, respectively. Let $\mathbf{x}$ be a sparse signal in an arbitrary domain (DCT domain) where we have a subset of its samples in another domain (time domain). The DT operator is used for transforming the signal from the sparsity domain to the time domain. To initialize, the signal is estimated as an all-zero matrix. After taking the discrete transform of the signal, sparsity is enforced by using an adaptive threshold which keeps the components above a specific threshold value. In order to retrieve all the coefficients of the signal, the threshold is set to a large value at first and decays exponentially as the iteration number increases (the reverse can also be performed)as:

$$\theta(k) = \theta(0)e^{-\alpha k} \tag{3}$$

The inverse discrete transform of the thresholded coefficients are interpolated and the exact time domain samples of the signal are replaced. After a number of iterations in time and frequency domain, the estimated signal becomes more similar to the original one.

4 DISTRIBUTED RANDOM SAMPLING AND RECOVERY

In the distributed random sampling technique, various non-overlapping binary masks are designated to each of the sensor nodes according to a predefined template. The block diagram of the distributed random sampling scheme is depicted in Figure 1.

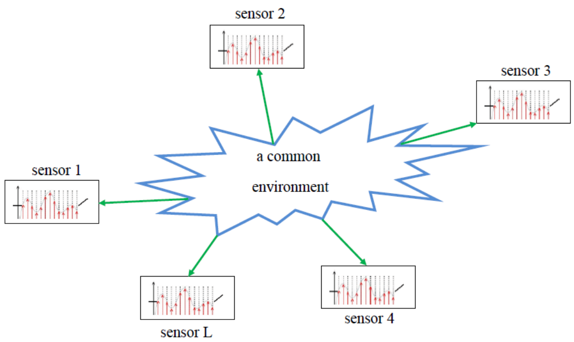

Figure 1: The distributed sampling block diagram.

For the recovery process, we can consider two topologies, the star topology and the ring topology.

The star topology for centralized recovery

In this scenario, the nodes are sending their samples to a Fusion Center (FC) which recovers the signal using the method suggested in the previous section. The block diagram of the star topology for centralized recovery is shown in Figure 2.

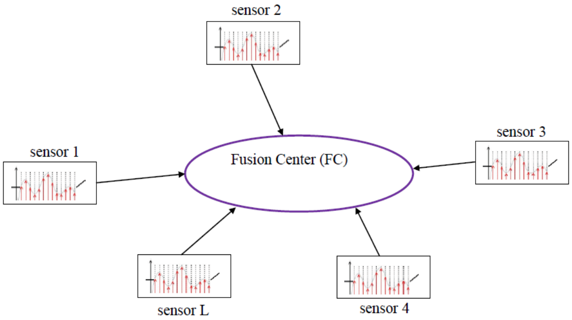

Figure 2: The star topology for centralized recovery.

In this case, the sampling is done in a distributed way, while the recovery procedure which might be more complex and energy-consuming is conducted in a centeralized manner. This scenario can be helpful in the applications where the available energy of the sensor nodes are too low that they cannot perform the recovery. Moreover, the samples taken from different sensors are corrupted by independent noises and their sum in the FC achieves diversity and hence the SNR is increased. As an application of this scenario can be the use of several low-cost microphones to improve the SNR of an audio signal by an amount of 10*log(L) dB where L is the number of distributed microphones. We have verified this fact by simulating two microphones and observing 3 dB improvement.

The ring topology for disributed recovery

In this scenario, we try to distribute the reconstruction task between different sensors. The block diagram of the ring topology for the distributed recovery is depicted in Figure 3.

The first sensor applies some iterations of the RS recovery method and sends the result to the second sensor which uses the recovery of the previous sensor as an initial condition for the recovery of its subset of samples. The third sensor which applies the recovery procedure on the received signal from the second sensor produces the ultimate recovery of the signal. In this way, we implement the signal sampling and recovery in a progressive and distributed way. This scenario can be used in the applications where the nodes have the ability to do a part of the recovery task. The

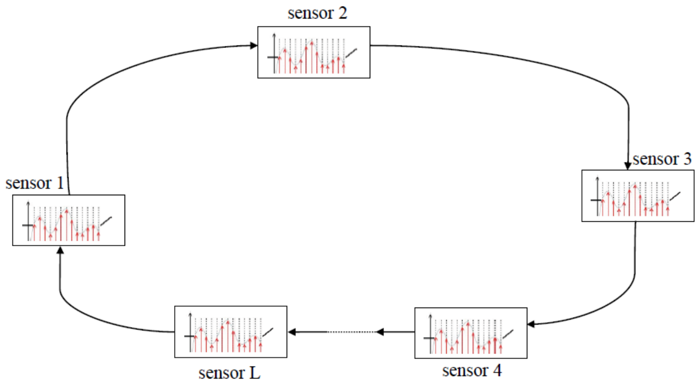

Figure 3: The ring topology for ditributed recovery.

advantage of this scheme compared to the previous one is that no FC is required in this case.

5 conclusion

In this position paper, we proposed a sampling technique to be used in the nodes of a wireless sensor network. The suggested scheme relies on the random sampling methodology. Furthermore, we presented two different scenarios for the recovery process in the network. By using the star topology, the sampling is done in a distributed manner, and the recovery is conducted in a fusion center. The ring topology, however, provides the distributed IMATI recovery algorithm where the complexity burden is divided between various network nodes.

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