Wavelet-based Energy Efficient Data Collection Algorithm in Wireless Sensor Networks

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Abstract—Wireless sensor networks (WSNs) support many applications in different fields. Saving energy in such networks is always a critical issue that needs to be considered to prolong the network lifetime. Clustering in the networks is also considered as an energy saving routing method. In this paper, we propose a new data collection method, called WDC, in order to significantly reduce data transmitting among clustered networks for energy saving purpose. In the method, Wavelet basic is employed in each cluster to compress data to be sent to the base-station (BS). At the BS, all the sensing data can be reconstructed based on the compressed samples collected from clusters. We further analyze and formulate the total energy consumption for data transmitting between sensors in the networks and from the networks to the BS. Simulation results are provided to clarify our analysis and to suggest optimal cases for the network to consume the least power.

Keywords—Wireless sensor networks; data compression; clustering, energy consumption; Wavelet basic.

I. INTRODUCTION

RECENT years, many research studies in wireless sensor networks (WSNs) take a lot of attention since the networks have many applications [1], [2]. Tracking objects or detecting events are very common applications in different fields. Sensors are deployed randomly in a forest to detect fire [3], [4]. They can be deployed in a sensing field to rescue people or to detect oil leak [5], [6]. In other cases, sensors are also deployed to build scalar maps [7], [8], [9] for data analysis purposes. The maps are built based on raw data collected from all sensors in the sensing fields. WSNs are embedded with different topologies. They could be dynamic or fixed structures depending on the purposes of such networks. Cluster-based [10], [11], tree- based [12], [13], gossip-based [14], [15], random walk [16], [17], etc. are very common data collection methods applying in the networks. Each method has prominent points to be utilized for specific applications. Wireless connections have some options including Bluetooth, Wi-Fi, RF in which they are suitable in applications [18], [19], [20], [21].

Clustering algorithms are considered as an energy saving data collection methods in the networks [11]. K-means [22], LEACH [23] are common methods to divide the network into clusters. K-means optimizes the transmitting distances between cluster-heads (CHs) and non-CH sensors to reduce energy consumption for sensors. LEACH chooses CHs based on stochastic theory to balance energy in the network since the biggest work load always falls on CHs. Many other clustering algorithms have shown their energy-efficient points for WSNs [24], [25], [26], [27]. Clusters could be arranged unequally in order to balance the consumed energy between clusters since the ones close to the BS always spend more energy than the one farther.

In this paper, we apply Wavelet transform theory for clustering in WSNs to compress sensing data in each cluster. In a clustered network, each cluster has one cluster-head (CH) and the rest are non-CH sensors. All non-CH sensors send their own data to the CH they belong to. This CH multiplies the collected data including its own data to Wavelet coefficients and only sends the large transformed coefficients to the base- station (BS) or the data processing center. The BS collects the large coefficients from all clusters following that way and reconstructs all data from the clusters to be able to build a scalar map. We further propose different ways to forward the transformed coefficients from CHs to the BS; the coefficients are forwarded directly to the BS or relayed between other CHs to finally reach the BS. Energy consumption for data transmission in the networks is formulated.

The remainder of this paper is organized as follows. Problem Formulation and Energy Consumption Analysis are addressed in Section II and III, respectively. Simulation results are provided in Section IV. Finally, Conclusions and future work are in Section V.

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II. Problem Formulation

A. Network Model

We assume N sensors randomly distributed with an equal probability in a sensing area. N_c clusters are pre-chosen for the network. So, N_c CHs are randomly chosen from all the sensors based on a probability N_c/N. This can share the burden of workload of being CHs for every sensor. Then, the rest as non-CH sensors choose one CH which is closest to form clusters. On average, each cluster has $\left(\frac{N}{N_c}\right)$ sensors. And each CH has $\left(\frac{N}{N_c}-1\right)$ non-CH sensors. As shown in Figure 1, non-CH sensors send directly data to their own CHs. Each CH processes the collected data within its cluster and sends a certain number of samples to the BS for data reconstruction following the Wavelet-based data compression (WDC) algorithm.

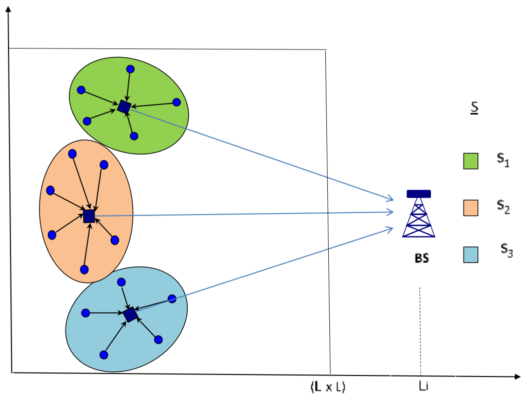

Figure 1. Sensor readings are transmitted from sensors to cluster-heads (CHs) and finally to the base-station (BS).

B. Wavelet-Based Data Compression Algorithm for Clustered WSNs (WDC)

As mentioned the previous sections, the network is divided into N_c cluster. Figure 1 shows the clustered network in general with the BS outside the sensing area. Generally, all non-CH sensors send their data to the CHs. All the CHs forward all the received data including their own to the BS.

In the proposed algorithm, each CH creates one Wavelet sub-matrix ϕ_i with dimension $(n_i \times n_i)$, where n_i is the number of sensors in the i^{th} cluster. Data collected at each cluster is multiplied to a sub-matrix in which, all the entries are created by the Matlab command $haarmtx(n_i)$. A large proportion of the signal energy is focused on the very first large coefficients, given as K coefficients. Only these coefficients are sent to the BS from all the CHs. The remainder of the transformed coefficients can be considered as zeros. Only $K = \sum_{i=1}^{N_c} k_i$ large coefficients are sent instead of N scalar sensig values that significantly save energy for transmitting data in the network. The trade-off of the proposed method will be discussed in the Simulation results section. The WDC algorithm can be written in short as in Algorithm 1.

In formula, the transformed coefficients at the cluster i^{th}, represented as a vector s_i, are calculated as

$$s_i = \phi_i x_i. \quad (1)$$

The number of the large coefficients taken from each cluster should be proportional to the number of sensors as

$$\frac{k_i}{K} = \frac{n_i}{N} \quad (2)$$

where n_i represents the number of sensors in the cluster i^{th}. The BS obtains the readings from the i^{th} cluster based on s_i' which is created from the received k_i large coefficients and additional zeros as

$$\hat{x}_i = \phi_i^T s_i' \quad (3)$$

The proposed algorithm can also work well with fault tolerance in the network since all sensors take turns to become CHs. Malfunction nodes are not chosen after each round of choosing CHs or non-CH sensor nodes. The faults of the network or sensor nodes could be detected and recovered by fault tolerant algorithms for clustered networks [28] or for tree-based networks [29]. Malfunctioned nodes are isolated but could be used for relaying data in the network if possible. This could be an open work for our future research.

Algorithm 1
Wavelet-Based Data Compression Algorithm for Data Collection in Wireless Sensor Networks (WDC)

1. Clustering phase

- Number of clusters are pre-defined as Nc

- The WSN is divided in to Nc clusters following LEACH [23]

2. Data compression phase

- Each CH collects data within its cluster including its own data

- The CHs multiply the raw data with Wavelet coefficients

- A certain number of large coefficients (*K* samples) are chosen to be sent to the BS.

3. Forwarding data to the BS

- k_i samples from i^{th} cluster (CHi) are sent to the BS with two options:

(i) The coefficients are sent directly to the BS, or

(ii) The coefficients are forwarded through intermediate CHs to the BS.

4. Data reconstruction phase

- The BS collects the large coefficients from *Nc* clusters

- *K* samples are multiplied to Wavelet coefficients to return the raw data from the network.

III. Energy Consumption Analysis

Energy consumption for transmitting and receiving data in WSNs [30], denoted as P_{Tx} and P_{Rx}, are formulated, respectively as

$$P_{Tx} = P_{T_0} + P_A(d), \quad (4)$$

and

$$P_{Rx} = P_{R_0}. \quad (5)$$

P_{T_0} and P_{R_0} are two energy consumption levels of electrical elements for coding, modulating or signal processing. They do not depend on transmitting distances, denoted as d. In this paper, we only consider the consumed energy of the power amplifier $P_A(d)$ which is a function of d. The total energy consumption for transmitting data in such networks contain two parts. Energy consumed for non-CH sensors to transmit their readings to the BS. It is called the intra-cluster energy consumption, denoted as $P_{intra-cluster}$. The consumed energy for all CHs to transmit the large transformed coefficients to the BS is denoted as P_{toBS}.

A. $P_{intra-cluster}$ Analysis

As assumed, a uniformly distributed WSN is divided into N_c non-overlapped clusters with the same number of sensors as N/N_c, consisting of one CH and $\left(\frac{N}{N_c}-1\right)$ non-CH nodes. We have:

$$P_{intra-cluster} = N_C\left(\frac{N}{N_c}-1\right)E[r^\alpha], \qquad (6)$$

where r is a random variable which represents distances between non-CH sensors to CHs they belong to, and α is the path loss exponent. As mentioned in [31], $\alpha = 2$ or 4 in free space or multiple fading channels, respectively. α is chosen to be 2 throughout the paper. We can calculate $E[r^2]$ as follows:

$$E[r^2] = \iint (x^2+y^2)\rho(x,y)dxdy \qquad (7)$$

$$= \iint (r'^2)\rho(r',\theta)r'dr'd\theta. \qquad (8)$$

in which $\rho(x,y)$ is the node distribution. Similar to [32], we assume that each cluster area is circular with radius $R = L/\sqrt{\pi N_c}$ and the density of the nodes is uniform throughout the cluster area, i.e. $\rho(r',\theta) = 1/(L^2/N_c)$. As calculated in [33], [34], we obtain

$$E[r^2] = \frac{L^2}{2\pi N_c}, \qquad (9)$$

and the total intra-cluster energy consumption

$$P_{intra-cluster} = \left(\frac{N}{N_c}-1\right)\frac{L^2}{2\pi} \qquad (10)$$

We can see that the total intra-cluster energy consumption is a decreasing function of the number of clusters.

***Note**: in case the sensing area is circular, $P_{intra-cluster}$ is calculated in [35] as

$$P_{intra-cluster} = \left(\frac{N}{N_c}-1\right)\frac{R_0^2}{2}, \qquad (11)$$

where R_0 is the radius of the sensing area.

B. $P_{to\,BS}$ Analysis

We assume that all the clusters have the same number of sensors. We show that the number of large coefficients taken from a cluster are linearly proportional to the number of sensors in that cluster. Hence, in our analysis case, the number of large coefficients collected from N_c clusters should be equal. The total number of large coefficients is calculated as

$$K = \sum_{i=1}^{N_c} k_i = N_c k_i\ , \qquad (12)$$

where k_i is the number of coefficients collected from cluster i^{th}. We consider both ways to forward the large coefficients to the BS, transmitting directly or forwarding through intermediate CHs based on a routing tree.

1. Large coefficients are directly transmitted to the BS: As shown in Figure 1, the average consumed energy for all CHs to transmit K large coefficients to the BS is

$$P_{to\,BS} = KE[d^2]\,, \qquad (13)$$

where d is the random variable representing the distance between CHs and BS. Assuming that all CHs are randomly distributed in the entire area to balance the energy consumption for the network, the expected squared distance between CHs and the BS [36] is given by

$$E[d^2] = \int_0^L\int_0^L \left[(x-L_i)^2 + \left(y-\frac{L}{2}\right)^2\right] f(x,y)dxdy \qquad (14)$$

$$= \frac{1}{L}\left[\frac{(L-L_i)^3}{3} + \frac{L_i^3}{3}\right] + \frac{L^2}{12}, \qquad (15)$$

where $f(x,y) = \frac{1}{L^2}$ is the uniform distribution of CHs in the sensing area.

From Equations (10) and (15), the total energy consumption in this method can be formulated in general as:

$$P_{total} = \left(\frac{N}{N_c}-1\right)\frac{L^2}{2\pi} + \frac{K}{L}\left[\frac{(L-L_i)^3+L_i^3}{3}\right] + \frac{KL^2}{12}. \qquad (16)$$

When the BS is at the center of the sensing area ($L_i = L/2$), Equation (15) is simplified as $E[d^2] = \frac{L^2}{6}$, and the total energy consumption for the network is

$$P_{total} = \left(\frac{N}{N_c}-1\right)\frac{L^2}{2\pi} + \frac{KL^2}{6}. \qquad (17)$$

***Note**: if the sensing area is circular and the BS is at the center, $P_{to\,BS}$ is calculated in [35] as

$$E[d_{toBS}^2] = \frac{R_0^2}{2}. \qquad (18)$$

Hence, the total energy consumption is

$$P_{total} = \left(\frac{N}{N_c}-1\right)\frac{R_0^2}{2} + K\frac{R_0^2}{2}\ . \qquad (19)$$

2. Large coefficients are transmitted to the BS utilizing inter-cluster multi-hop routing:

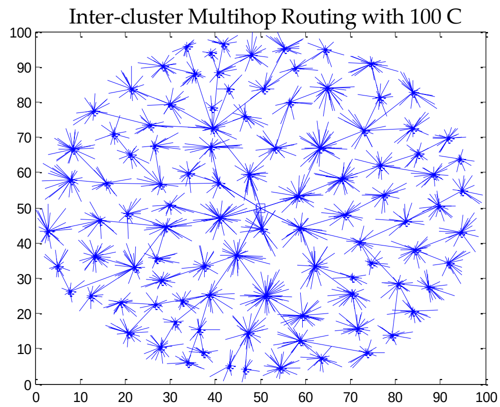

Figure 2. Cluster-heads (CHs) transmit or relays the Wavelet coefficients through others to the base-station (BS) utilizing multi-hop routing.

As shown in Figure 2, all sensors are randomly deployed in a circular sensing area with the BS at the center. Since CHs are randomly chosen from the sensors based on a probability N_c/N, they are also randomly distributed in the area. We assume to have an algorithm to form a routing tree connecting all the CHs with the root as the BS at the center of the sensing

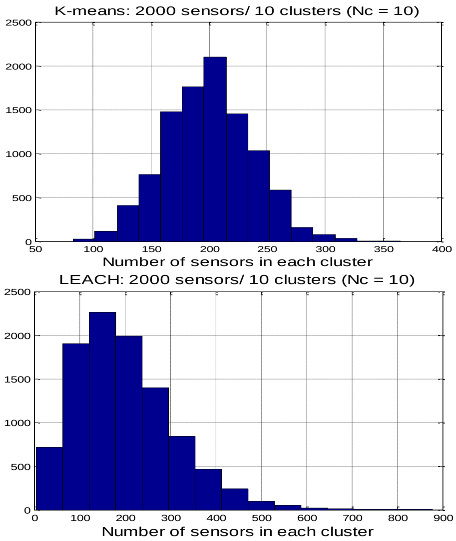

Figure 3. Histograms from two clustering algorithm Kmeans and LEACH in the network with 2000 sensors distributed in a square area 100 × 100

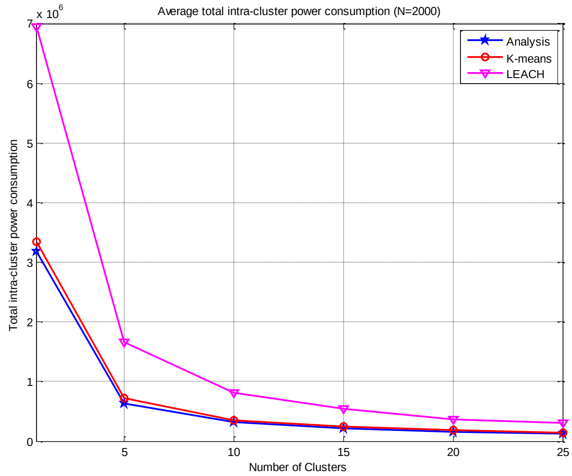

Figure 4. Comparison of total intra-cluster energy consumption for the networks deployed Kmeans, LEACH and Analysis with 2000 sensors randomly distributed in a square area 100 × 100

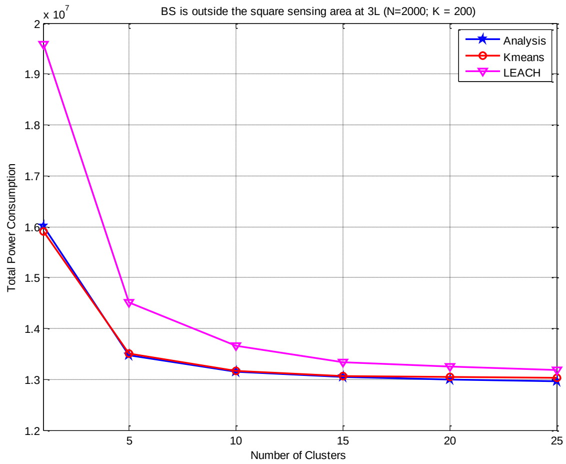

Figure 5. Total energy consumption for all data transmissions in the network with 2000 sensors partitioned into different number of clusters when the BS is outside the sensing area at 3L

area as mentioned in [35]. The distance between a random CH and the BS can be considered as a random variable, denoted as x. The probability of being able to make a connection at distance x using $hops$ or less hops is denoted by $P_{hops}(x)$. In paper [37] the mean value of the number of hops ($hops$) is calculated as follows

$$E[hops] = max(hops) - \sum_{n=1}^{max(hops)-1} \frac{P_{hops}(x)}{P_{max(hops)}(x)} \quad (20)$$

where $max(hops)$ is the maximum number of hops allowed. Finally, we obtain the total consumed energy for relaying K large coefficients from CHs to the BS as

$$P_{toBS} = \left\{hops_{max} - \sum_{hops=1}^{hops_{max}-1} \frac{P_{hops}(x)}{P_{max(hops)}(x)}\right\} R^2 K, \quad (21)$$

where R is the CH's transmission range. This value can be changed depending on the CH density. In other words, if the number of CHs reduces, we need to increase R to maintain all CHs connected as a routing tree. We have the total energy consumption for data collection in the entire network using multi-hop relaying as

$$P_{total} = \left(\frac{N}{N_c} - 1\right)\frac{L^2}{2\pi} + E[hops]R^2K. \quad (22)$$

From Equations (17), (19) and (22), the total communication power consumptions are the linear functions of the number of large coefficients K.

IV. Simulation Results

We consider both common types of networks, square sensing area with dimension 100×100 and circular area with radius $R_0 = 50$. In each network, there are 2000 sensors randomly deployed. K-means [22] and LEACH [23] are also deployed to collect data and to compare with our analysis results. Real sensor readings collected from Sensorscope [38] are used for simulating. We evaluate the total energy consumption for the networks and provide the performance of the proposed algorithm with the data. The normalized reconstruction error $\frac{\|x-\hat{x}\|_2}{\|x\|_2}$ is applied.

In Figure 3, a comparison shows a histogram of the number of sensors in each cluster created by two algorithms, Kmeans and LEACH. Kmeans provides more uniform size for clusters than LEACH does, which results in the smaller intra-cluster energy consumption on average, as shown in Figure 4. In other words, the shorter the transmitting distances are, the smaller the energy consumption inside clusters.

The total consumed energy for the network to transmit data to the BS at the position of $L_i = 3L$ is shown in Figure 5. Since the total number of large coefficients is chosen as $K = 200$, this power is decreased as we increase the number of clusters following the intra-cluster energy consumption.

In order to work in the circular sensing area with multihop routing, we use a greedy algorithm proposed in [35] to form a routing tree between CHs. At each network divided into

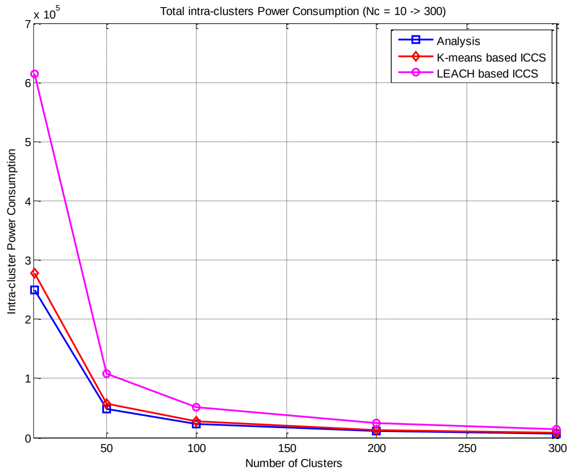

Figure 6. Total intra-cluster energy consumption for the network with 2000 sensors distributed in a circular sensing area with radius $R_0 = 50$

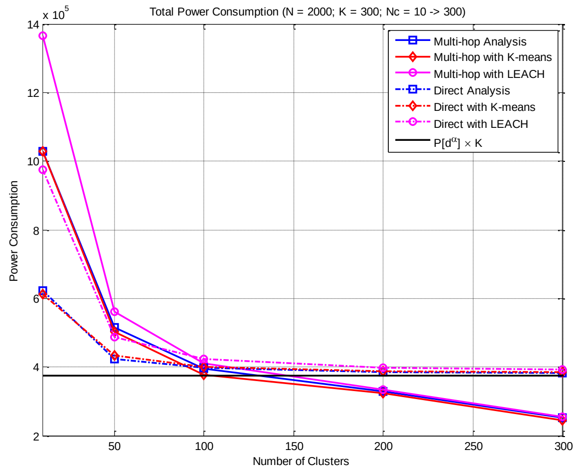

Figure 7. Total energy consumption for all transmissions in the network using inter-cluster multi-hop to forward K large coefficients the the BS in a circular sensing area with radius $R_0 = 50$

different numbers of clusters, we use different transmission ranges $R = [50\ 30\ 25\ 22\ 18]$ corresponding to $N_c = [10\ 50\ 100\ 200\ 300]$. Figure 6 shows the intra-cluster power consumptions calculated from K-means, LEACH and the analysis case. Kmeans minimizes the intra-cluster power consumption. So the energy consumption from the network arranged by Kmeans are very close to our analysis results since we assume that all clusters have an equal size. Figure 7 shows and compares the total energy consumptions for both methods, direct and multi-hop to forward the coefficients to the BS. It is shown that, if the numbers of clusters are small, the direct method still consumes less power than the multi-hop method. As the number of clusters is greater than 150, the multi-hop routing methods consumes less energy than the direct one.

Figure 8 shows real sensor readings as scalar values and Figure 9 shows their Wavelet transformed coefficients in frequency domain. All signal energy is preserved in the transformed vector but is now focused in relatively small

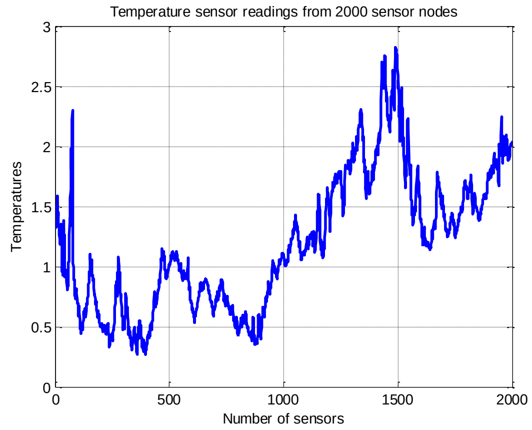

Figure 8. Sensor readings as temperatures collected from 2000 sensors

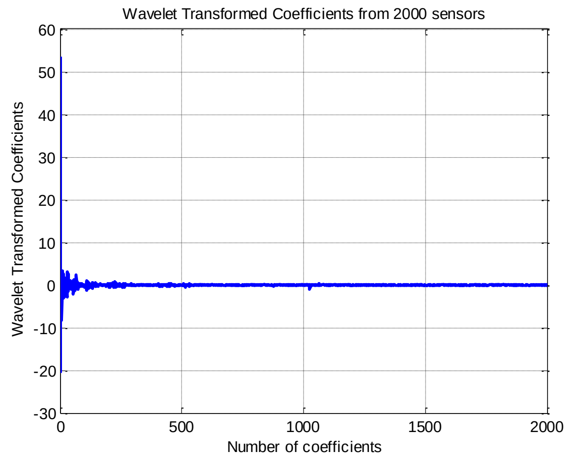

Figure 9. 2000 Wavelet transformed coefficients created from 2000 real sensor readings; only large coefficients are collected to be sent to the BS.

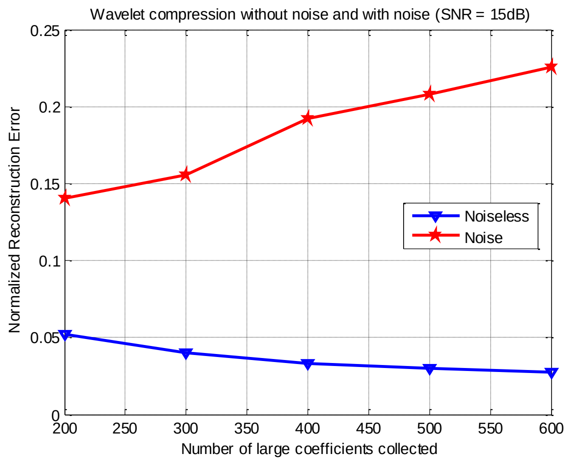

Figure 10. Wavelet compression reconstruction error versus the number of large coefficients with noise and noiseless

numbers of large coefficients. If we transmit only these K large valued coefficients to the BS, this results in much less consumed power than transmitting all the readings.

In a noiseless environment, using Wavelet-based compression can save significantly energy since the networks only send K large transformed coefficients ($K \ll N$). As shown in our simulation results, K needed is only about 10% to 20% of N to satisfy an error-target in signal recovery processes. In practical networks, noise is problematic. Wavelet compression degrades quickly as shown in Figure 10. The reconstruction errors keep increasing as the number of large coefficients increases. So, noise in the system should be considered.

V. Conclusions and Future Work

In this paper, we proposed Wavelet based data compression algorithms (WDC) for clustered WSNs to reduce energy consumption in collecting sensory data. Based on the fact that almost all data energy focused in relatively small numbers of large coefficients in the transformed vector, we only send the large coefficients to the BS for the signal recovery process. These coefficients are mapped at the BS to recover all sensory readings from the network. We analyzed and formulated either the intra-cluster energy consumption or the total consumed energy for the network to transmit data. Simulation results are provided for both consumed calculation and the wavelet compression method. We concluded that this Wavelet compression method degrades its performance when working in noisy environment. We suggest an optimal case for the networks to use multi-hop if many clusters are applied. In future work, we will study the boundary for the number of clusters in both noise and noiseless environments.

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