Power Aware Image Transmission in Energy Constrained Wireless Networks

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Abstract

We consider transmitting images in a multi-hop wireless network with the minimal total power consumption while satisfying an end-to-end image quality constraint. Contrary to popular belief, we show that maximum compression before transmission does not always provide minimal energy consumption, especially in the case of dense sensor networks with complex signal processing algorithms. We formulate the minimal energy transmission problem as an optimization problem and present a heuristic algorithm for it. The proposed algorithm selects the optimal image compression parameters to minimize total energy dissipation given the network conditions and image quality constraints. Simulation results show up to 80% reduction in the total power consumption achieved by using the proposed adaptive algorithm compared to non-adaptive algorithms.

1. Introduction

Wireless sensor networks are being developed for a variety of applications such as surveillance, environmental monitoring and smart spaces [8]. Energy management in these networks is crucial since battery-driven sensor nodes are severely energy-constrained. The two factors that affect the energy consumption of the sensor network are communication and computation. One of the design choices that must be made in sensor networks is the balance between local computation and the communication of data back to the processing center.

Currently, most energy-constrained wireless networks are designed with the objective of minimizing the communication power at the cost of more computation, since it is usually more significant in the total system power consumption [8]. The energy consumption due to computation has been considered negligible. However, in the case of a dense multi-hop network, the energy needed for communication decreases dramatically due to the relative small distance between nodes. Recently, visual sensor networks [5] are emerging and introducing new challenges beyond those common to most other sensor networks, such as acoustics, temperature or pressure. For instance, image coding requires high computation power, and makes computation energy comparable to computation energy.

In this paper, we consider the problem of minimizing the energy dissipation for transmitting images over a multi-hop network subject to a specific image quality constraint. We formulate it as an optimization problem. Considering the effects of varying parameters of a wavelet based image compression algorithm on total energy consumption and image quality, we introduce a heuristic algorithm to select the optimal image compression parameters to minimize total energy dissipation given the network conditions and image quality constraints. Simulation results show significant reduction in the total energy consumption compared to non-adaptive algorithms.

Up to our knowledge, energy efficient image transmission in multi-hop wireless networks has not been studied in the literature. However, our work has been inspired by a variety of other research efforts. In [7], an adaptive image compression algorithm was proposed for mobile multimedia services. The impacts of the multi-hop and random error wireless link on the received image quality and total energy consumption, are not studied. While previous research [10] has studied the effects of adapting the channel coder to physical layer constraints, the effects of adapting source coder have not been studied for multi-hop networks. Recently, [3] shows that there is a net energy saving when compression is applied before transmission. It is worth noting that they focus on lossless data compression which is different from, (and can be considered a special case of,) the image compression techniques considered here.

The remainder of the paper is organized in the following way. Energy consumption models for computation and communication are provided in Section 2. The analysis results are presented in Section 3. We present our adaptive algorithm in Section 4. Experiments and simulation of the proposed adaptive algorithm are presented in Section 5. Finally, Section 6 presents conclusion and future work.

2. Models and Scenarios

In this section, we describe the network model, the image transmission applications considered in this paper and the energy consumption models.

We consider a multi-hop wireless sensor network which consists of camera-equipped nodes and a processing center. A node can respond to the query of the processing center by generating a fixed size raw image (e.g. a snapshot of its sensing area) and compressing/coding the raw data using an image compression algorithm before transmitting to the processing center.

We make the following assumptions:

- All nodes have the same radio range d.
- The underlying wireless network is modelled as a n hop path, denoted by $S_1 \rightarrow S_2 \rightarrow \ldots \rightarrow S_n \rightarrow C$.
- When sending a query, the processing center specifies the desired image quality Q_d[1].
- A cluster based routing infrastructure is in place. The cluster head may perform intermediate data processing if specified by the application.
- The communication environment is contention-free but not error-free. The channel in every hop is modelled as an independent and identically distributed (IID) random bit error channel with error probability p_e[2].

Throughout this paper we do not take into account the energy consumed at the processing center which is commonly assumed to be not energy limited.

Figure 1 shows the block diagrams of a node as sender and receiver. Every node has source (image) encoder/decoder and wireless transceiver module.

The primary candidates of wireless communication for sensor networks are currently radio frequency (RF) or optical [6]. For this study, we use a simple transceiver model [12]. The power consumed to transmit a distance d per bit,

$$E_{TX}(d) = \epsilon_e k + \epsilon_{amp} k d^{\alpha} \tag{1}$$

1 Image quality is often measured using a metric know as the Peak Signal-To-Noise Ratio (PSNR), which is defined as (in decibels)

$$PSNR = 20log_{10}\frac{2^b - 1}{E\|x(i,j) - \hat{x}(i,j)\|}$$

where $x(i,j)$ is the pixel value of original image, $\hat{x}(i,j)$ is of the reconstructed image and b is the bit-depth (bpp) of the original image. We recognize the PSNR does not always accurately model perceptual image quality, but use it because it is a commonly used metric in the literature.

2 We argue that channels exhibiting correlated errors (e.g. fading) can be transformed to this model using channel coding schemes (e.g. interleaving and channel coding can be used in burst-error and fading channels) [9].

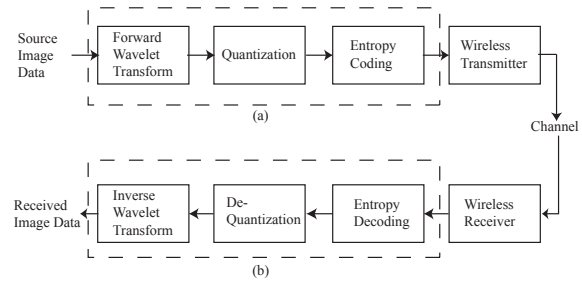

Figure 1. Block diagrams of sender (top) and receiver (bottom).

where ϵ_e is the energy per bit dissipated in the transceiver circuit, ϵ_{amp} is the energy per bit dissipated in the transmit amplifier and α is the path loss parameter. The power consumed in receiving per bit,

$$E_{RX} = \epsilon_e k. \tag{2}$$

In optical transmission, only transmitting consumes power (i.e. power consumed in reception can be neglected). It is also shown in [6] that the average transmitted energy per bit and distance are related by $E_b \propto d^2$ if other parameters are fixed. Thus, the above model is still applicable to optical links if we choose proper parameters ϵ_e and ϵ_{amp}.

We consider JPEG2000, a variable rate image compression scheme that uses both lossy and lossless compression. The compression ratio can be controlled by the transform (decomposition) level and quantization level [4]. The main block diagrams of the wavelet-based image encoder and decoder are also shown in the dashed rectangles in Figure 1 (a) and (b) respectively. Increasing the applied wavelet transform level can increase the compression ratio, leading to less bits to be transmitted. However, it results in an increase of computation energy. Let $\epsilon_c(L)$ denote the energy consumed per bit as a function of transform level L.

$$\epsilon_c(L) = \gamma(f - 4^{-L-1}), L = 0, \ldots, L_{max} \tag{3}$$

where γ is device and implementation specific constant value, L_{max} is the possible maximum transform level which is determined by image size and f is a factor caused by quantization and entropy coding [7]. Let β denote the compression ratio (compressed data size over original data size). Since compression ratio is source related (depends on source characteristics), in order to isolate the impact of transform level, we empirically derived the following equation where the compression ratio is only dependant on L by experiments which is described in Section 5.

$$\beta(L) = \frac{g_1}{g_2 - g_3^{-L}}, L = 0, \ldots, L_{max} \tag{4}$$

where g_1, g_2 and g_3 are empirically derived parameters. Thus, to compress 1 bit of raw image to achieve compres-

sion ratio $\beta(L)$, we need

$$E_c(L) = \epsilon_c(L) \tag{5}$$

Decompressing these compressed $\beta(L)$ bits will consume almost the same energy as compressing without rate control [4].

3. Analysis

We analyze two typical scenarios of image transmission across a multi-hop wireless network: Case 1, intermediate nodes act only as relays; Case 2, intermediate nodes may fuse multiple images into a single image before relaying.

3.1. Case 1: no intermediate data processing

A sensor generates k bits of raw image data after receiving a query from the processing center which specified the required image quality. It compresses this image at wavelet transform level L to achieve compression ratio $\beta(L)$ then sends the image to the processing center via a multi-hop path. In this case, the intermediate nodes do nothing except forwarding data to the processing center. The total power consumption for transmitting this image to the processing center is:

$$E_{total} = kE_c(L) + nk\beta(L)[E_{TX}(d) + E_{RX}] \tag{6}$$

3.2. Case 2: intermediate data processing

Although details of intermediate data processing clearly depend on the specific characteristics of applications, we try to identify some common principles that can be applied to sensor networks across various applications. In order to save communication energy, a cluster head may locally compress (or, more accurately, fuse) the images from different sensors together, thus reducing the total number of bits to be transmitted. To the best of our knowledge, estimation of correspondence between a set of images is a fundamental and difficult problem in computer vision [13], which is not in the scope of this paper. However, the cluster head must first de-compress the data to process it *and* then re-compress it again before transmitting it to the next cluster. To account for fusion at intermediate nodes in this case, we assume that when the total incoming data size at an intermediate cluster-head is k bits, the output will be δk bits. The total power consumption for a cluster head that runs a multi-image compression (fusion) is

$$E_{total} = 2kE_c(L) + nk\beta(L)\delta[E_{TX}(d) + E_{RX}] \tag{7}$$

It is worth re-emphasizing that the above analysis does not account for the energy dissipated in generating the raw images (i.e. capture) and estimating the correspondence between images (part of the fusion process).

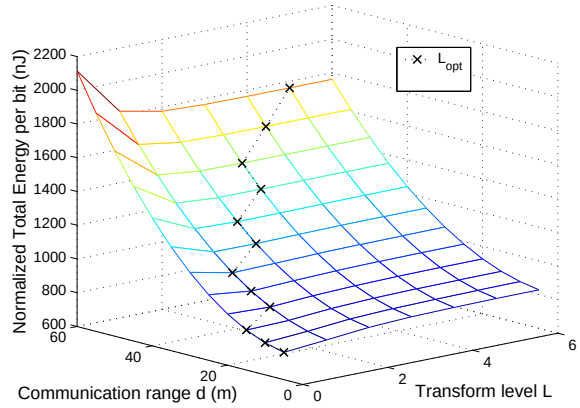

Figure 2. Normalized total energy consumption per raw image bit as a function of transform level L and communication range d. $n = 15, \delta = 0.5$, RF transmission, Case 2. Observe that total energy is monotonically non-decreasing when $L \geq L_{opt}$.

The network optimization problem can now be formally stated as follows:

$$\begin{array}{ll} \textit{minimize} & E_{total} \\ \textit{subject to} & 0 \leq L \leq L_{max} \\ & Q_r \geq Q_d \end{array} \tag{8}$$

where Q_r is the PSNR quality of received image. As shown in Figure 2, there exists an optimal value L_{opt} which minimizes E_{total} for different values of the communication range d. For example, $L_{opt} = 3$ when $d = 45m$ and $n = 15hops$.

4. A Heuristic Algorithm

Although the above optimization problem (8) can be solved by a centralized, nonlinear optimization method, the computation complexity associated with a centralized approach is high and prohibits us from using it in this instance. In this section, we develop a heuristic distributed algorithm, MTE (abbreviation for "Minimize Total Energy"), to minimize the total energy consumption.

Before describing the algorithm itself, we discuss the assumptions needed for implementing it;

1. Source node S_1 knows an estimate of the total number of hops n to the processing center;
2. Each node S_i is aware of its own communication and computation energy cost (1), (2) and (3).

The first assumption can be achieved by embedding the number of hops of the communication path in the query from the processing center. Or the source node S_1 may get

this information from underlying routing layer or knowing the location and the sensor density. The justification of the second assumption is that ϵ_e and ϵ_{amp} are device-dependent and can be obtained from the radio device configuration, while d, α, γ and f are system-aware parameters which can be determined during the sensor network deployment stage.

The algorithm works as follows. In the first step, the algorithm determines the parameter of quantization and the wavelet image compression transform level to meet the image quality requirement. Normally, the end-to-end image quality is affected by two factors: quantization and transmission error due to wireless channel. Also compressed image is more vulnerable to transmission errors compared to raw image. For example, the received image Figure 3(b) can only achieve PSNR of 27dB through a link with $p_e = 10^{-4}$, while the raw image Figure 3(a) can achieve PSNR of 45dB through the same link. It is even worse in the case of multi-hop communication path. We found that the maximum allowed value L'_{max} may be smaller than L_{max} due to a long (n is large) and bad (p_e is high) path for a high image quality requirement (large Q_d). In this paper, we choose a simple method to determine the quantization level and possible transform level set. We generate a table by running extensive simulations on image samples for every configuration of quantization, transform level and path. A node can check this pre-computed table to determine the quantization level and possible transform level set ($[0, \ldots, L'_{max}]$) for a given network and image quality constraint[3].

(a) PSNR of received raw image = 44.58dB.

(b) PSNR of received compressed ($L = 6$) image = 26.58dB.

Figure 3. Comparison of raw vs. compressed image through a channel with $p_e = 10^{-4}$.

In the second step, the initial value of L is set to zero for each sensor. After the image is captured, the sensor S_1 compresses this image using wavelet image compression. The sensor computes the compression ratio β (and, in Case 2, δ), and calculates the total energy dissipation (using both computation and communication energy models) E_{total}. Then, the sensor increases L by 1, runs wavelet image compression to compute the new value of β (and δ for Case 2), computes new value of total energy dissipation and compares it with the old value. The above steps will be repeated if the new value of E_{total} is smaller than old value and L is less than some maximum allowed value L'_{max} (recall that L'_{max} is obtained in step 1). Otherwise, this procedure will stop and return the value of L which is the optimal value that minimizes the total energy.

An alternative that helps reduce the computation requirement for iteratively calculating E_{total} is through a pre-computed lookup-table, where interpolation for approximated results may be used to reduce the size of the table. In this case, energy consumption for each possible combination of the parameters (transform level, quantization and communication path length) are calculated on image samples. Then, given the network and application constraints such as transmission medium, communication range and image quality, a table lookup is performed to identify the set of parameters (transform level and quantization) that satisfy the application requirements. Another alternative to reduce this computation cost is letting the processing center calculate the value of optimal parameters. In this way, the processing center can compute optimal parameters for a queried node if the processing center has information about the routing path to the destination node. However, the accuracy of compression ratio in these off-line methods is not as good as on-line algorithm since we average over a set of test images instead of the actual image being transmitted.

5. Experimental and Simulation Results

In this section, experiments to derive the values of the parameters in our models (3), (4) and performance evaluation of our heuristic algorithm are presented.

To verify our model and determine f and γ in (3), we have employed *JouleTrack* [11] to estimate the energy consumption for an existing JPEG2000 coder[4] [1]. The experiment data in terms of total energy spent by a StrongARM SA-1100 processor are measured when running JPEG2000 image compression algorithm at 206 MHz with different transform levels L on test image *Lena* (512x512). Parameters f and γ in (3) are calculated using MATLAB for this experiment data. We believe that it is reasonable to expect similar curves from other types of processors. We also estimated the energy consumed in running our adaptive algorithm and found it is negligible compared to the image com-

3 There are some complex and on-line methods to determine the quantization level and channel codec over an error channel for a given end-to-end image quality requirement [2].

4 All options of this JPEG2000 coder are the default values except transform level L which is chosen from 0 to 8. To isolate the impact of transform level on compression ratio, rate control is turned off when compressing.

Parameter	Optical	RF
α	2	2
ϵ_e	0	$50nJ/bit$ [12]
ϵ_{amp}	$0.2nJ/bit/m^2$ [6]	$0.1nJ/bit/m^2$ [12]

Table 1. Parameters of wireless communication energy model in (1) and (2)

γ	f	g_1	g_2	g_3
$0.23549\mu J/bit$	1.1947	1.1211	3.2219	3.5424

Table 2. Parameters of image compression energy model in (3) and (4)

pression. Thus, we omit the cost for our adaptive algorithm in the energy consumed for computation. Since the compression ratio is source related (depends on source characteristics), we calculate average compression ratio $\beta(L)$ on a set of reference images. They are popular test images *Lena* (512x512), *Goldhill*(512x512), and two JPEG2000 test images *Cafe* (2048x2560) and *Bike* (2048x2560). Then parameters g_1, g_2 and g_3 in (4) are calculated using MATLAB from this experiment data. Parameters of wireless communication energy model are shown in Table 1. Parameters of image compression energy model are shown in Table 2.

We ran extensive simulations to decide the quantization level and possible allowed value of transform level for different choice of n and Q_d. Figure 4 shows an example simulation results on image sample (*Lena*) for different values of n. We observe that the quality requirement Q_d restricts the possible range of values of L. For example, when $n \geq 35$, $Q_d = 25dB$ and $p_e = 10^{-6}$, L'_{max} can only be 5 even though $L_{max} = 6$. When the channel is worse ($p_e = 10^{-5}$), $L'_{max} = 6$ and hence $Q_d \leq 15dB$, i.e. the received image will be low quality for a far away source node.

The optimal setting of image transmission in both RF and optical wireless sensor networks are simulated using our MTE algorithm. Due to the space limitations, only one figure for each case is shown here (similar results were observed for other cases). Figures 5 and 6 show that the optimal selection of transform level L is dependent on the number of hops n and the communication range of each hop d. For free space optical transmission, Figure 5, the optimal setting of L is "maximum compression" only when the number of hops is large or the communication range is large. We consider Case 2 in Figure 6 where a cluster-head performs intermediate data processing/fusion. Even for RF transmission, the results show that the optimal setting is not fixed at maximum compression.

The comparison of the energy consumption achieved by using our adaptive algorithm against a static algorithm is shown in Figure 7. 1000 sensor nodes are randomly placed in a field of 200m $\times$ 200m. The processing center is placed at the corner of the field. Every sensor is assumed to send

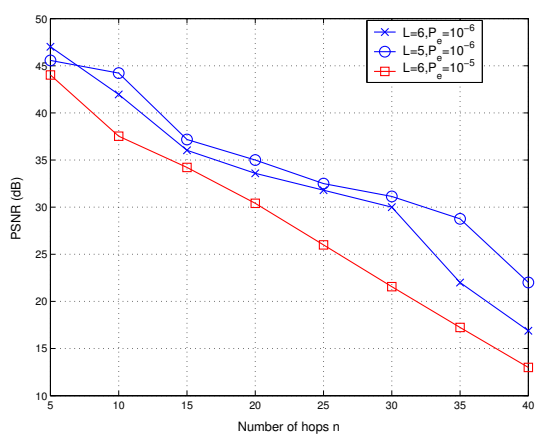

Figure 4. PSNR of received image (Lena) vs. number of hops n.

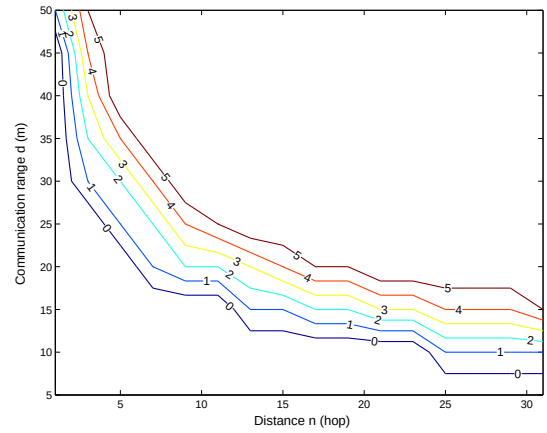

Figure 5. Contour of optimal transform level L as a function of n and d. Optical transmission, Case 1. Observe that maximum compression is effective only when n or d is large.

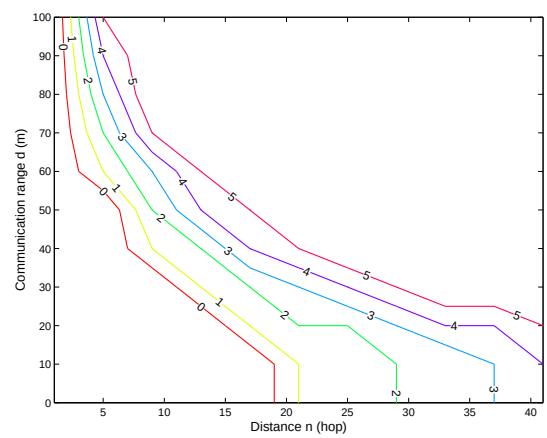

Figure 6. Contour of optimal transform level L as a function of n and d. RF transmission, $\delta = 0.5$, Case 2. Observe that maximum compression is not optimal in a considerably large range of n and d.

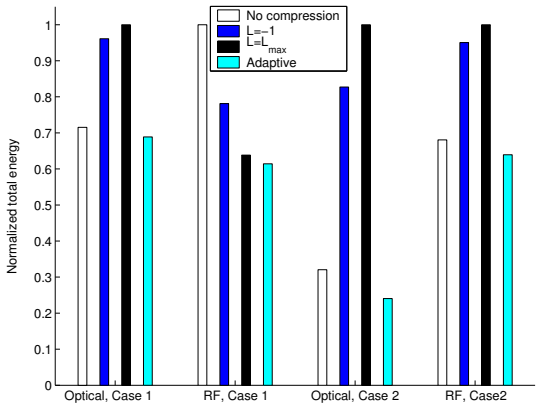

Figure 7. Energy comparison: adaptive vs. static. $d = 10m$, $\delta = 0.5$ in Case 2. $L = -1$ means performing entropy coding directly on raw image without wavelet transform. In all cases, adaptive algorithm performs best in terms of total energy consumption.

one image to the processing center along a shortest path. The image quality requirement Q_d is 20dB. The channel error probability p_e in every hop is 10^{-6}. Average total energy dissipation over all sensors is computed. The results show that considerable energy gain (up to 80% savings in energy) can be achieved when using adaptive algorithm. We can also see that maximum compression before transmission is only effective for a very large sensor network using RF in Case 1.

6. Conclusion and Future Work

This paper studied the problem of energy-efficient image transmission in multi-hop wireless sensor networks. Both RF and free-space optical are considered as the underlying wireless transmission media. Contrary to popular belief, we found that computation power consumption is a fairly significant share of total energy consumption and hence it is also important in the design of energy-aware image-based applications in sensor networks. Simulation results show that the proposed adaptive algorithm can save significant energy while satisfying the performance constraint (i.e. a target image quality) compared to traditional approaches that employ maximum compression. The contribution of this research is not merely to show that one can use an adaptive algorithm to achieve a certain reduction in energy, but also to show that the choice of whether and to what extent to compute (image compression as an example) is not obvious. The tradeoff between communication and computation deserves more attention and investigation in designing data rich wireless sensor networks with sophisticated computation.

Several extensions of the problem studied in this paper are worth further investigation. From a protocol perspective, variations of the proposed on-line mechanism can be developed for improved robustness and performance. From application perspective, one extension is to consider other computation algorithms in wireless sensor networks, such as video coding. Another extension is to investigate the energy tradeoff of distributed computation over multiple sensor nodes.

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