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Cross-layer Energy Optimization Under Image Quality Constraints for Wireless Image Transmissions

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Abstract

Wireless image transmission is critical in many applications, such as surveillance and environment monitoring. In order to make the best use of the limited energy of the battery-operated cameras, while satisfying the application-level image quality constraints, cross-layer design is critical. In this paper, we develop an image transmission model that allows the application layer (e.g., the user) to specify an image quality constraint, and optimizes the lower layer parameters of transmit power and packet length, to minimize the energy dissipation in image transmission over a given distance. The effectiveness of this approach is evaluated by applying the proposed energy optimization to a reference ZigBee system and a WiFi system, and also by comparing to an energy optimization study that does not consider any image quality constraint. Evaluations show that our scheme outperforms the default settings of the investigated commercial devices and saves a significant amount of energy at middle-to-large transmission distances.

Index Terms

Energy consumption modeling; image quality; cross-layer optimization; wireless transmissions

I. Introduction

Wireless image transmission is important for a variety of applications, from security and surveillance to in-home monitoring. However, wireless imagers are battery-operated, and hence the energy-efficient design of these systems is critical to their operation. Most existing studies on energy optimization of wireless communications consider error-free packet transmission, where the entire packet has to be retransmitted if there is even a single bit error. However, for image transmission applications, there is often a certain tolerance to errors in the received data, as errors in the decoded data become distortion in the image content. In this paper, we derive a cross-layer model of the energy consumption of wireless imagers. Using this model, we can jointly optimize the transmit power at the physical layer, and packet retransmissions and the packet length at the MAC layer, while meeting an image quality constraint issued by the application layer.

Consider the following image transmission procedure: after source coding an image, the resulting information bits are packetized based on a *packet length*, and then sent to the receiver with a specific *transmit power*. The receiver will determine the error rate in each received packet. We define an internal system parameter δ to represent *the packet-level error-tolerance rate*. If the error rate of a packet exceeds δ, a retransmission of the packet is requested. The image constructed at the receiver side using the accepted packets is required to have a higher image quality than the image quality constraint issued by the application layer. Fig. 1 shows the image transmission process.

Considering this procedure, we propose a system model that determines the energy per image as a function of the distance to the receiver, the packet length, and the transmit power. Additionally, using the model in [1] we can relate the packet-level error-tolerance rate to the peak signal-to-noise ratio (PSNR) of the reconstructed image. Note that for a coded image like JPEG that has dependencies, an error in the coded data may cause different quality degradation if it occurs at different locations in the data. Thus, we only consider the average PSNR for all received images, as done in [1], taking into consideration different quality degradations. Given the energy model and the image quality degradation model, we can determine the optimal packet length and transmit power that minimize the energy per image given an application-level PSNR constraint on the reconstructed image.

II. Related Work

Although there are several studies to minimize the energy consumption with transmit power control [2], or packet length optimization [3], or based on a distortion constraint [4], [5], our work is the first one to consider all of these design criteria to derive a cross-layer joint optimization, and an internal packet-level error-tolerance parameter is defined to relate the image quality constraint to packet-level optimizations.

In [6], the authors consider the joint optimal design of the physical, MAC, and routing layers to maximize the lifetime of energy-constrained wireless sensor networks. However, their work does not consider the impact of the application layer on energy saving. Our work takes advantage of the user-defined image quality constraint, making the energy minimization problem more flexible while satisfying the application level requirements.

The joint energy optimization problem in terms of adjusting both packet length and target bit error rate (BER) has been studied in [7], where the authors assume that the data must be received error-free. However, this restriction is not required for multimedia applications, where a user's requirements may vary. Thus, it is imperative to also consider the application level quality requirement and relax the error-free transmission constraint in the optimization.

In [4], image quality is evaluated in terms of distortion observed in the application layer. The authors build a comprehensive power-rate-distortion optimization framework for image sensors. However, in that framework, retransmissions are not considered. If an intra or inter macroblock is lost, the previous macroblock is repeated as the current one. Also, users do not have control over the received image quality. In our work, on the other hand, retransmissions are considered, and the users can define their own received image quality requirement.

Joint optimization of the application layer, data link layer, and physical layer is studied in [8] using an application-oriented objective function in order to maximize user satisfaction. However, our goal is to reduce the total energy consumption instead of maximizing the user satisfaction.

III. Cross-Layer Energy Consumption Modeling and Energy Minimization

In this section, we present the cross-layer energy minimization problem for the communication of images over wireless links. There are three controllable parameters we consider: the payload length L_L, the transmit power P_t, and the packet-level error-tolerance rate δ. As we will show in this section, the energy consumed to transmit an image depends on these parameters and the transmission distance d. Our goal is to minimize the energy consumption per image by finding the optimal values for these three controllable parameters to meet a given PSNR threshold, $PSNR_g$, for a given transmission distance, d_g. Also, in practice, the payload length is limited by different factors, such as application level data rate, latency constraints, and the allowable packet length limits introduced by the MAC layer. Accordingly, we define the maximum value of a payload length to be L_{max}. The optimization problem can then be expressed as

$$\begin{aligned} \min_{\{P_t, L_L, \delta\}} \quad & \overline{E}_{image}(P_t, L_L, \delta, d), \\ s.t. \quad & PSNR(P_t, L_L, \delta, d) \geq PSNR_g, \\ & d = d_g, \\ & 0 < L_L \leq L_{\max}, \\ & P_t > 0, \\ & \delta \geq 0, \end{aligned} \quad (1)$$

where $\bar{E}_{image}$ is the average total energy for successfully transmitting and receiving one image, and $PSNR_g$ is the given PSNR threshold of the system, which denotes the requested received image quality. In the following sections, we derive the mathematical formula for $\bar{E}_{image}$, and we present the relationship between image quality and the communication distortion.

A. Packet structure and energy consumption model

The packet structure consists of payload, upper layer header, PHY/MAC-header, and preamble, the size of which are L_L, L_{UH}, L_H and L_P bits, respectively. In this paper, we assume that the entire packet is modulated using uncoded Binary Phase Shift Keying (BPSK) and that the transmit power is constant during the entire packet. Also, the upper layer header, PHY/MAC-header and preamble are assumed to be protocol-dependent fixed length components. Hence, we only need to optimize the length of the payload.

We look at minimizing the total energy consumption required per one image. Let V denote the image size in pixels, L_L the payload length, and R the source coding rate in bits per pixel (bpp). The number of packets forming the image is, then, $\frac{V \cdot R}{L_L}$. If this value is not an integer, the remaining data is packetized into a packet of payload size less than L_L.

If we let $\bar{E}_{pkt}$ denote the average energy consumption for successful transmission of a packet, the total energy for successfully transmitting and receiving one image can be expressed as $\overline{E}_{image} = \frac{V \cdot R}{L_L} \cdot \overline{E}_{pkt}$. There are four energy components of $\bar{E}_{pkt}$: transmission energy E_{tx}, transmitter circuit energy E_{ct}, receiver circuit energy E_{cr}, and source coding energy E_{sc}. Let P_{ct} and P_{cr} represent the power for the transmitter circuits and receiver circuits, respectively, and T_{on} (L_L) denote the time the nodes must remain in the *on* state for one successful or unsuccessful transmission of a packet. Then, the three communication energy components are formulated as

$$E_{tx} = P_t \cdot T_{on}; \quad E_{ct} = P_{ct} \cdot T_{on}; \quad E_{cr} = P_{cr} \cdot T_{on}, \quad (2)$$

where P_t is the transmit power. Note that all three energy components are functions of T_{on}, and hence, of L_L. We assume the source coding energy, E_{sc}, is constant and cannot be optimized, for the sake of simplicity.

We consider a point-to-point transmission over an additive white gaussian noise (AWGN) channel with no fading or interference from other transmissions. For AWGN channels, the bit error rate P_b can be approximated as a function of transmit power P_t and distance d:

$$P_b(P_t, d)=\frac{1}{2}e^{-\frac{P_t}{2B\,N_0}\cdot\left[\frac{\sqrt{G_l}\lambda}{4\pi\,d}\right]^{3.5}}, \quad (3)$$

where we assume a path loss exponent of 3.5 and B is the signal bandwidth, N_0 is the noise power spectral density, G_l is the product of the transmit and receive antenna gains, and λ is the wavelength.

The *on* time of nodes is calculated as $T_{on}=T_L+T_{UH}+T_H+T_P=\frac{1}{R_b}\cdot(L_L+L_{UH}+L_H+L_P)$, in which T_L, T_{UH}, T_H and T_P refer to the transmission time for the payload, upper layer header, PHY/MAC layer header and preamble, respectively. R_b is the bit rate and equals to the signal bandwidth B for uncoded BPSK modulation. Therefore, T_{on} is a function of our optimization parameter L_L.

In the case that a packet needs to be retransmitted, the energy consumption for data transmission and transceiver circuits power should be multiplied by n, i.e., the total number of transmissions (including the first transmission). However, we do not need to multiply E_{sc} by n, since we do source coding to the original image once before transmission. Therefore, if the number of transmissions for a single packet is n, the total energy is

$$E_{pkt}(n)=n\cdot T_{on}(L_L)\cdot[P_t+P_{ct}+P_{cr}]+E_{sc}. \quad (4)$$

For the *error-tolerance control*, we define a packet-level error-tolerance rate variable, denoted as δ. This internal system parameter is adjusted based on the *allowed image quality level* assigned by the application layer. Considering the commonly employed selective repeat ARQ in our model, if the bit error rate of a received packet is less than or equal to δ, then the packet is accepted and passed to the upper layers. Otherwise, the received packet will be discarded, and a NACK is sent to the transmitter to request a retransmission of the packet. Mathematically, the maximum number of errors in a single packet that can be tolerated at the receiver is then $\lfloor(L_L + L_{UH})\,\delta\rfloor$, where $\lfloor\bullet\rfloor$ is the floor function. All packets with less than or equal to $\lfloor(L_L + L_{UH})\,\delta\rfloor$ errors are accepted, thus the probability of accepting a received packet is the summation of all the possibilities of having less than or equal to $\lfloor(L_L + L_{UH})\,\delta\rfloor$ errors, which can be formulated as:

$$Pr_{acc}=\sum_{i=0}^{\lfloor(L_L+L_{UH})\delta\rfloor} C^{i}_{L_L+L_{UH}}(1-P_b)^{L_L+L_{UH}-i}P_b^i, \quad (5)$$

where i is the number of errors in the packet.

As stated above, n denotes the total number of transmissions for the successful reception of a packet. The expected value of n, N, is then

$$N=E[n]=\sum_{n=1}^{\infty}n\cdot Pr_{acc}(1-Pr_{acc})^{n-1}=\frac{1}{Pr_{acc}}. \quad (6)$$

Therefore, by taking the expectation of E_{pkt} given in (4), the average total energy consumption is

$$\overline{E}_{image}=\frac{V\cdot R}{L_L}\cdot\{N\cdot T_{on}\cdot[P_t+P_{ct}+P_{cr}]+E_{sc}\}. \quad (7)$$

Plugging (3), (5) and (6) into (7), we obtain the total energy to transmit an image as a function of transmit power, P_t, packet payload length, L_L, transmission distance, d, and the packet-level error-tolerance rate, δ.

B. Mathematical relationship between error-tolerance rate and received image quality

In the previous section, we modeled the average total energy per image $\bar{E}_{image}$ with a tolerable error rate δ. In this section, we further study the impact of δ, and the communication distortion on the received image quality.

While δ is the error-tolerance threshold per packet, it is not a performance metric and does not evaluate the overall quality of the received data directly. On the other hand, the average bit error rate of all *accepted* packets, BER_{acc}, does. Given an overall accepted packet BER, BER_{acc}, we need to consider how the randomly distributed channel bit errors in the received image influence the overall image quality. In this paper, we investigate JPEG compressed images as the application source, for which a joint source-channel distortion model is presented in [1]. The authors derive the overall image distortion caused by quantization during source coding and by channel bit errors, assuming 8-bit unsigned representation for unquantized pixel values. Also, data is in the form of a stream in [1], and not packetized. Thus, P_b is directly used to calculate the channel errors. However, in our study, we use retransmissions to guarantee the received packets' quality in terms of bit error rate in the packet. Thus, at the receiver end, we use BER_{acc} instead of P_b to calculate the impact of random bit errors that are caused by the channel on the received image quality, which is different from [1]. We fix the source coding rate R to 1.25 bpp and only focus on the impact of channel distortion on the image quality. We will explore different source coding rates in our future work.

To use the PSNR image quality model presented in [1], we need to derive the average bit error rate of all *accepted* packets BER_{acc}. Let the variable i denote the number of errors in a received packet. The average BER among all accepted packets is then

$$BER_{acc}(P_t, L_L, \delta, d)=\frac{\sum_{i=0}^{\lfloor (L_L+L_{UH})\delta\rfloor} i\cdot C^{i}_{L_L+L_{UH}}(1-P_b)^{L_L+L_{UH}-i}P_b^i}{(L_L+L_{UH})\cdot Pr_{acc}}, \quad (8)$$

where the numerator is the average number of errors for accepted packets, which is normalized by the packet acceptance probability Pr_{acc} in the denominator.

By plugging (7) into (1), the energy minimization problem formulation is derived, where PSNR is a function of BER_{acc} (defined in (8)) as presented in [1].

IV. Energy Optimization Results

In this section, we obtain the optimal P_t, L_L and δ tuple, i.e., (P_t^*, L_L^*, δ^*) for the energy optimization problem in (1). The importance of such an optimization is presented by comparing the default behavior and the optimized behavior of a ZigBee commercial mote and a WiFi commercial mote. The investigated modules are Crossbow's MICAz mote [9] and Microchip's ZG2100M/ZG2101M transceiver module [10], respectively. Since optimization parameter L_L is an integer, the resulting mixed integer programming problem is not a convex problem. Thus, standard methods like the Karush-Kuhn-Tucker approach or Lagrange multipliers cannot be used to obtain the optimal solution. Instead, we find the optimal solutions by using numerical optimizations in MATLAB.

A. Numerical evaluation setup

To evaluate the effect of the optimization parameters on the performance of a real life communication system, we first define the communication parameters to be the same values as those used in the MICAz motes [9], but keep the transmit power P_t and the payload length L_L as variables. The carrier frequency is $f_c = 2.4$ GHz, the transmit data rate is $R_b = 250$ kbps, the upper layer overhead length for ZigBee is $L_{UH} = 160$ bits, the PHY/MAC layer header length is $L_H = 32$ bits, the preamble length is $L_p = 32$ bits, and the maximum payload length is set to $L_{max} = 10^5$ bits, which is 12.5 KB. The transmit circuit power is set to $P_{ct} = 11mA \times 3V = 33mW$, which is the lowest power level used for data transmissions according to the MICAz specifications. Similarly, the receiver circuit power is set to $P_{cr} = 19.7mA \times 3V = 59.1mW$. Since the energy consumption for source coding E_{sc} is assumed to be a small constant compared to the communication energy, and it does not affect the results for our optimization problem, we simply neglect it. We assume that the transmitted image size is $V = 512 \times 512$ pixels, and fix the source coding rate to $R = 1.25$ bpp.

Based on the distortion model given in [1], $PSNR$ is determined by BER_{acc} and R. Since we fix the value of R to 1.25 bpp, $PSNR$ is only determined by BER_{acc}. Therefore, we can change the PSNR inequality constraint to a BER_{acc} inequality constraint as $BER_{acc} \leq BER_{acc}^{g}$, where BER_{acc}^{g} denotes the BER_{acc} value for $PSNR_g$ at $R = 1.25$ bpp found from [1].

The numerical minimization of the energy per image is done for a given image quality and transmission distance, and on a given range of the payload length L_L, the transmit power P_t and the error-tolerance rate δ. The investigated error-tolerance rate interval is set to be from 10^{-7} to 10^{-1}. The search interval for an optimal payload length L_L is from 10 to 10^5 bits since $L_{max} = 10^5$ bits. Because the transmit power P_t is a function of P_b and d (see (3)), instead of running the brute-force search on a range of P_t values, we run on P_b values and then calculate the optimal P_t from the optimal P_b. The searching range for P_b is 10^{-7} to 10^{-1}. We investigate the effects of different transmission distance values by varying d from 10 m to 150 m. The PSNR value ranges from 12.8 dB to 28.4 dB, according to the available PSNR value range given in [1].

B. Numerical solution for the energy optimization problem

In this subsection, we numerically find the optimal (P_t, L_L, δ) tuple, i.e., (P_t^*, L_L^*, δ^*), that yields the minimum energy per image, $\overline{E}_{image}^{*}$. We present the minimum energy values found for different PSNR thresholds and transmitter-receiver distances, d, along with the corresponding optimal system parameter values yielding the minimum energy.

The minimum energy per image $\overline{E}_{image}^{*}$ values achieved for different PSNR thresholds and transmitter-receiver distances, d, are shown in Fig. 2. As revealed in the figure, the minimum energy per image increases as the transmitter-receiver distance increases, which is expected since higher transmit power is needed to compensate for the larger path loss. Additionally, we can observe that the minimum energy per image also increases as $PSNR_g$ increases, i.e., if the user requires a better image quality, more energy is dissipated. We find that the optimal transmit power has a similar trend (not shown).

The optimal packet length, L_L^*, is found to always be the maximum possible value within the allowable range, i.e., L_{max}. The reason is that since the error-tolerance rate δ defines the ratio of the number of erroneous bits to L_L, as L_L increases, the number of allowable erroneous bits also increases. Thus, the effect of the packet overhead decreases. As a result, the higher the L_L value, the lower the energy per image. We also find that the optimal probability of error, P_b^*, decreases as $PSNR_g$ increases, since a better received image quality requires a lower bit error rate over the channel.

The simulation results show that the number of transmissions is very close to one for all optimal cases, which means that we just need to transmit the image once with appropriately configured parameters, and the received image quality will, on average, meet the user-defined PSNR requirement. The reason is found to be that retransmissions are a very energy-inefficient way to enhance the received signal quality. Simulations show that the P_b^*/δ^* ratio is always smaller than 1, which means that the error-tolerance rate at the receiver end is larger than the average BER over a noisy channel. Therefore, we have no retransmissions on average.

With the numerical solutions derived for the energy optimization problem, we can set P_t, L_L and δ values according to the user-defined PSNR requirement. However, due to the fact that we do not have retransmissions for optimal cases, we accept every received packet. Hence, there is no need to use sophisticated error detection codes to compute the number of errors in each received packet to decide whether it needs to be retransmitted. Yet, δ is an important intermediate variable of the optimization process, and used to determine the values for optimal P_t and optimal L_L.

C. Sensitivity analysis of the optimization parameters

In this subsection, we investigate how sensitive the *mean energy per image* is to the P_t, L_L and δ values, and the importance of choosing the optimal P_t, L_L and δ values to save energy. For all evaluations in this subsection, the PSNR threshold is set to 19.5 dB and d = 30 m. For each of the three analyzed parameters, we evaluate the energy performance by fixing one of the parameters while optimizing the other two parameters. We denote the resulting energy per image as $\overline{E}'_{image}$, since it does not represent the overall minimum energy value, which is derived by optimizing all three parameters. For example, to show the sensitivity of $\overline{E}_{image}$ to L_L, we plot $\overline{E}'_{image}$ at and around L_L^*, as shown in Fig. 3(a). As expected, $\overline{E}'_{image}$ has its minimum value at $L_{max} = 10^5$ bits. $\overline{E}'_{image}$ decreases monotonically as L_L increases, since the longer the packet, the smaller the overhead portion is, and thus the system is more energy-efficient.

Fig. 3(b) shows that $\overline{E}^*_{image}$ lies at P_t^*=18.6 mW. When P_t deviates to a larger value from P_t^*, $\overline{E}'_{image}$ increases, but very slowly. Since the PSNR threshold can be met by transmitting once using the optimal power, using a higher power is unnecessary. When P_t deviates to a lower value from P_t^*, $\overline{E}'_{image}$ increases dramatically, mainly due to the rapidly increasing number of retransmissions.

As depicted in Fig. 3(c), $\overline{E}'_{image}$ decreases as δ increases and remains the same when δ is greater than 0.002. This is because when the error-tolerance threshold is as loose as 0.002, almost every received packet is accepted. Thus, we have $P_b = BER^g_{acc}$. When the error-tolerance threshold becomes looser, since P_b cannot be any larger due to the PSNR constraint, a larger δ has no effect on the received packet quality. Hence, with constant P_b and L_L values and $N \cong 1$, $\overline{E}'_{image}$ is also constant when δ is greater than 0.002. Thus, all δ values equal to or greater than 0.002 are optimal values. Recall that we define δ* as the smallest value that gives the minimum energy.

D. Performance gain over error-free transmissions

In our approach, the received image quality is determined by both source distortion and channel distortion. Thus, it is necessary to compare the energy that our approach consumes with that consumed by error-free transmissions proposed in [7], under the same received image quality constraint. Due to different study criteria or problem settings, we cannot compare our work with other works mentioned in the Related Work Section. In [7], the image quality is only effected by source distortion. They minimize energy by optimizing L_L and P_b. For our approach, one PSNR value is mapped to several (P_b, R) tuples, as stated in [1]. Thus, we minimize energy by optimizing L_L, δ, and the (P_b, R) tuple. Fig. 4 compares the minimized energy per image under different image quality constraints. Our approach saves around 10–20% of the energy for middle to large distances. Thus, to achieve the same image quality, distributing distortion in both the source coding and transmission processes achieves lower energy than only allowing distortion in the source coding process.

E. Performance gain over ZigBee and WiFi systems with default parameters

The potential gains of using the proposed cross-layer joint optimization is quantified by comparing its results to the default MICAz mote parameter settings, provided in [9]. The reference case defines a fixed transmit power of $P_t^{\dagger}=19.2mW$, and a fixed packet length of 128 bytes. For the reference case, with a fixed L_L and P_t, δ is the only parameter that can be adapted to meet the PSNR constraints. We compare the energy consumption between the optimal case and the reference case for a sample PSNR requirement of 28.4 dB. As seen in Fig. 5, at short transmission distances, energy consumption for the optimal case increases slightly as d increases, due to the slight relative increase in transmit power compared with circuit power. For the reference case, energy consumption remains at a constant higher level, since with a fixed transmit power and a fixed packet length, energy per packet is also fixed. Therefore $\overline{E}_{image}$ is solely determined by the expected number of retransmissions. For small d, the reference P_t value is large enough, resulting in no retransmissions and thus a constant $\overline{E}_{image}$. At short distances, our optimized approach saves about 35% of the energy compared to the MICAz motes. At large transmission distances, $\overline{E}_{image}$ for the optimal case is still relatively small, while $\overline{E}_{image}$ for the reference case increases sharply. This is because at large distances, P_b easily becomes larger than the error-tolerance threshold for a fixed P_t. Thus, an enormous number of retransmissions are needed.

Compared with ZigBee motes, WiFi modules normally use higher data rate, larger transmit power, and longer packets. We set all parameter values to be the same as the Microchip motes [10] when conducting the performance comparison. The transmit data rate is $R_b = 2$ Mbps. The transmit circuit power is $P_{ct} = 379.5mW$, and the receiver circuit power is $P_{cr} = 280.5mW$. The Microchip motes use a fixed transmit power of $P_t^{\dagger}=128.7\ mW$, and a fixed payload length of 2048 bytes, giving $L_L^{\dagger}=16,384$ bits. Though using a higher transmit power, the WiFi module consumes less energy than the ZigBee mote to transmit the same size image, since the circuits consume less energy by running for a shorter time. Due to space limitations and a similar performance gain behavior, the WiFi performance comparison figure is not shown. At short distances, around 18% of the energy can be saved with our optimization framework. More importantly, a significant amount of energy can be saved for distances larger than 25 m using our optimization approach.

V. Conclusions

This paper investigates cross-layer energy minimization given image quality constraints for wireless image transmissions. We formulate an energy consumption model with tolerable channel bit errors and retransmissions, and then provide the optimal system parameters to minimize the energy consumption while meeting a certain application-level received image quality constraint. Simulation results show that the minimized energy per image increases as transmission distance and image quality requirements increase. To achieve the same image quality, distributing distortion in both the source coding and transmission processes achieves lower energy than only allowing distortion in the source coding process. Finally, our cross-layer optimization approach is shown to significantly reduce the total energy consumption compared with a ZigBee commercial mote, saving around 35% of the energy at short distances, and much more at middle-to-large transmission distances. Also, our approach saves 18% of the energy compared with a WiFi commercial mote for short distances, and significant energy for middle-to-large distances.

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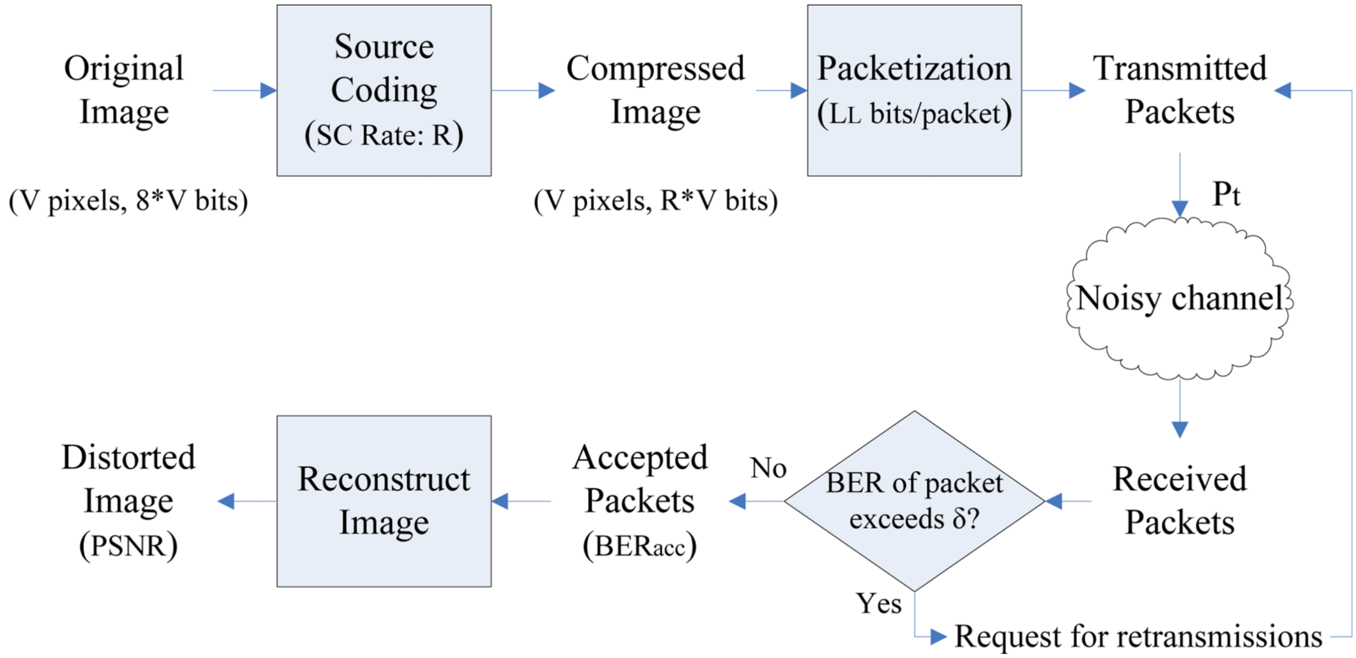

Fig. 1.
The image compression, transmission and reception processes.

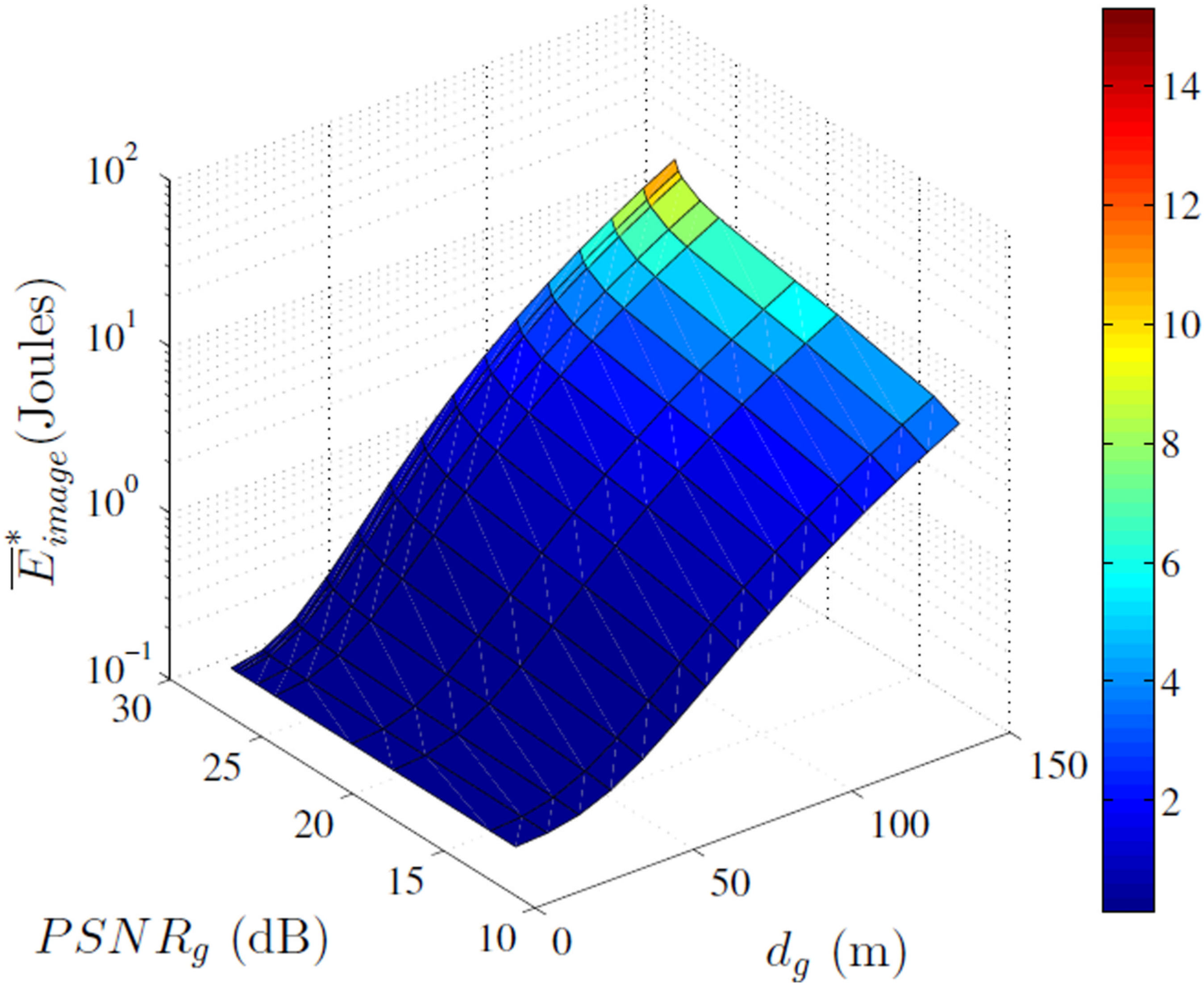

Fig. 2.
Minimum energy per image for varying *d* and PSNR threshold values.

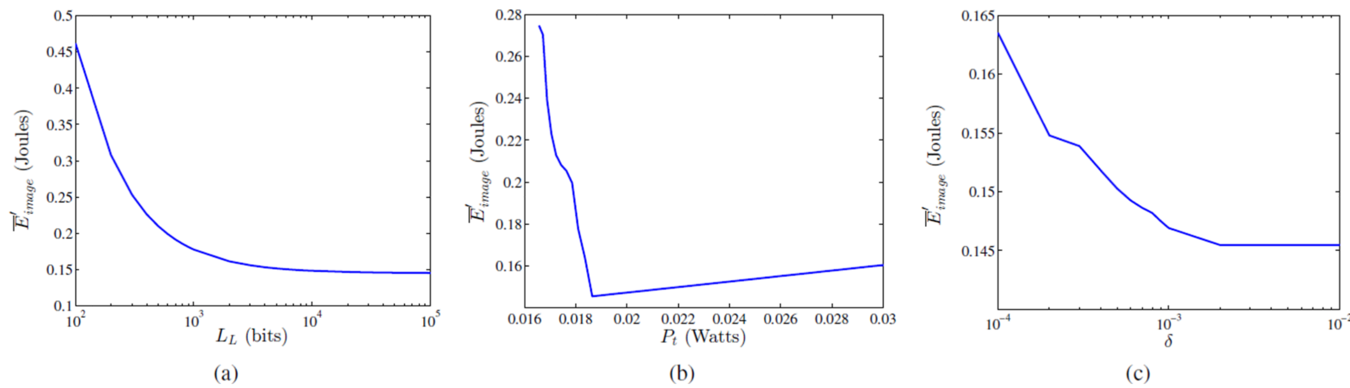

Fig. 3.
The sensitivity of $\overline{E}_{image}$ to a) L_L, b) P_t, c) δ.

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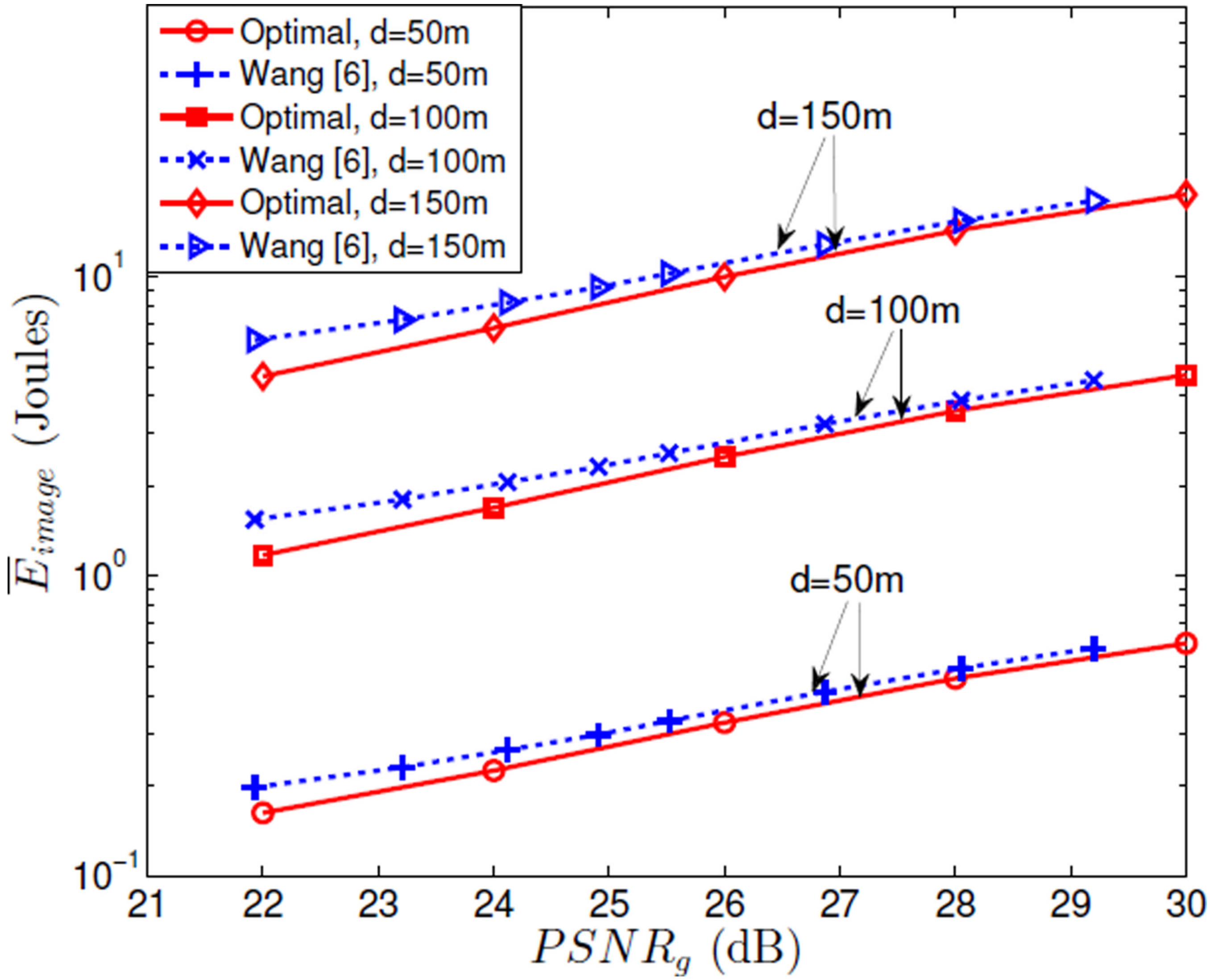

Fig. 4.

Energy performance comparison with [7].

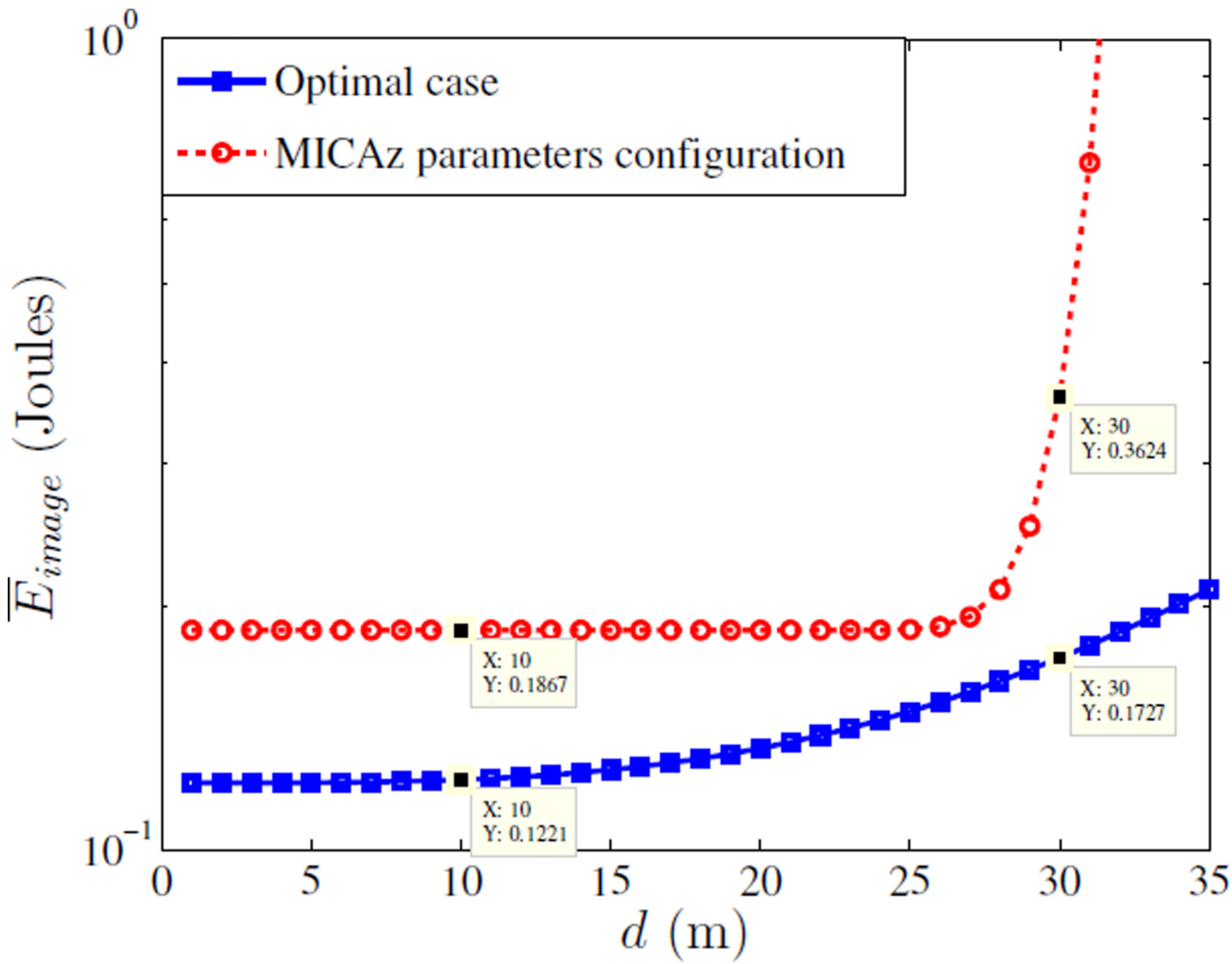

Fig. 5.
Energy consumption comparison with MICAz ZigBee motes at different transmission distances, for PSNR = 28.4 dB.