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Energy-Constrained Distortion Reduction Optimization for Wavelet-Based Coded Image Transmission in Wireless Sensor Networks

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***Abstract*—Image transmissions in Wireless Multimedia Sensor Networks (WMSNs) are often energy constrained. They also have requirement on distortion minimization, which may be achieved through Unequal Error Protection (UEP) based communication approaches. In related literature with regard to wireless multimedia transmissions, significantly different importance levels between image-pixel-position information and image-pixel-value information have not been fully exploited by existing UEP schemes. In this paper, we propose an innovative image-pixel-position information based resource allocation scheme to optimize image transmission quality with strict energy budget constraint for image applications in WMSNs, and it works by exploring these uniquely different importance levels among image data streams. Network resources are optimally allocated cross PHY, MAC and APP layers regarding inter-segment dependency, and energy efficiency is assured while the image transmission quality is optimized. Simulation results have demonstrated the effectiveness of the proposed approach in achieving the optimal image quality and energy efficiency. The performance gain in terms of distortion reduction is especially prominent with strict energy budget constraints and lower image compression ratios.**

***Index Terms*—Intra image diversity, cross layer optimization, unequal error protection, wireless sensor networks.**

I. Introduction

The availability of inexpensive hardware, such as Micaz plus Cyclops CMOS cameras and Stargate plus Logitech video cameras capable of capturing and transmitting multimedia content, has fostered the development of Wireless Multimedia Sensor Networks (WMSNs) [1]. Unlike traditional multimedia transmission in general wireless environments, communication energy efficiency is critical in WMSNs. However, multimedia data is usually bulk sized and contains diverse dependencies in bit streams, resulting in a significant challenge to design efficient transmission schemes over low cost WMSNs. In this paper, we specifically consider how to transmit wavelet-based compressed images with the best effort quality in WMSN under energy budget constraints, and propose a new position oriented resource allocation paradigm.

In general, the information of a natural digital image is conveyed by shapes and objects containing image pixels with various values, and wavelet based image compression schemes [2]–[4] can extract shape and position information of the regions as well as lighting magnitude information in regions. The wavelet coefficients with small magnitude values are often desirably compressed by significance propagation, dominant encoding, and run length based cleanup coding passes. As illustrated in Fig. 1, small-magnitude coefficients result in a large number of “0” bits in a bit-plane that can be efficiently compressed. The compressed small coefficients have avalanche error propagation effect since the errors in the number of consecutive “0” bits directly impact the positions of the large magnitude coefficients, leading to irrecoverable misalignment and decoding difficulty. These coefficients in small values stand for the image-pixel-position information. The output of magnitude refinement is related to the large value wavelet coefficients and corresponds to the image-pixel-value (i.e., brightness) information. As pointed out later in this paper, those large magnitude values themselves are relatively unimportant, but their locations are crucial for decoding and perception. These locations are determined by the process of compressing small-magnitude coefficients. The communication loss or errors in position information (p-data) will have significantly higher impact on the overall quality of the received image than the loss or errors in value information (v-data). The contribution of the research in this paper can be summarized in two aspects. First, we propose a new position based resource allocation paradigm with an effective position-value partition algorithm which is compatible to standard wavelet encoders. Second, the complex optimization problem is simplified and solved efficiently based on the position-value diversity.

The rest of the paper is organized as follows. Section II discusses the related research background. In Section III, the proposed position and value partition algorithm is presented and the cross layer optimization problem is formulated. In Section IV, the energy consumption, packet delivery quality and resource allocation strategies are modeled and mapped for each single image segment. In Section V, the cross layer optimization problem is simplified and solved based on the model proposed in Section IV. Simulation results are demonstrated in

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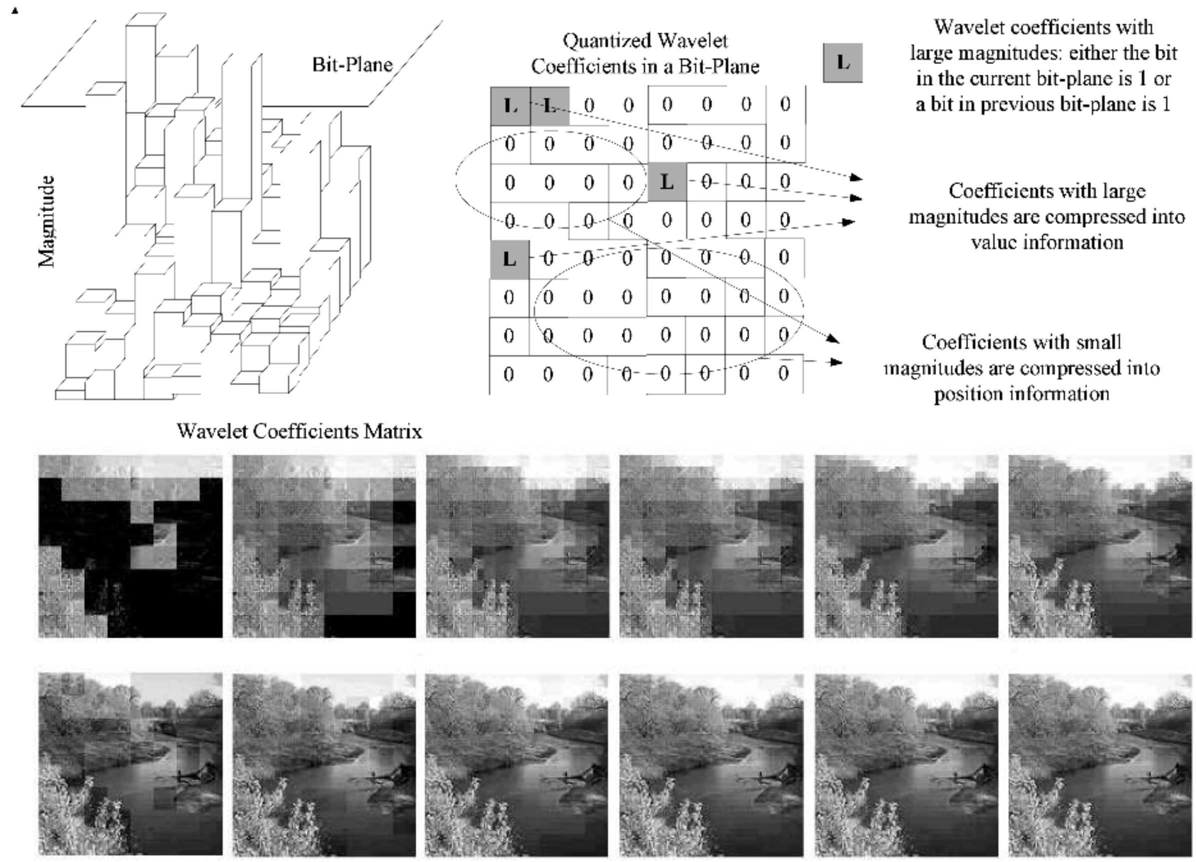

Fig. 1. This figure illustrates the unequal importance of position and value information. The diagram is the illustration of wavelet coefficients, bit-plane coding and the physical concept of the position-value information. Lower part images show the visual quality with erased p-data segments and v-data segment: The upper row shows the images with erased p-data segment in bit-plane 1–6 respectively, and the lower row shows the images with erased v-data segment in bit-plane 1–6, respectively.

Section VI. Finally, the conclusions are drawn in Section VII. The key notations used in the equations are summarized in Table I for reference convenience.

II. Related Works

Previous researches have been reported in the literature regarding cross layer resource allocation for wireless multimedia transmission, typically either via Automatic Retransmission reQuest (ARQ) based temporal Unequal Error Protection (UEP) or Forward Error Correction (FEC) based spatial UEP. However, the differentiation between position information and value information in the image bit stream has not been fully investigated.

In [5] Van der Schaar formalized a cross layer problem for delay sensitive and loss tolerant multimedia delivery over wireless networks. With explicit consideration of multimedia content and traffic characteristics, transmission strategies were jointly optimized across PHY, MAC and APP layers. In [6], Li proposed a retry limit adaptation scheme to achieve UEP for layer-coded video streaming over 802.11 based Wireless Local Area Networks (WLANs), where the video layers were protected over the wireless link with different ARQ retry limits. They further presented a classification and machine learning based system in [7] to predict the optimal MAC retry limits for various video packets. In [8], a cross layer problem was analyzed for distortion minimization given delay constraints, and the solution was derived through jointly adapting application layer packetization and priority based scheduling into MAC layer retransmission strategy. Other similar works can be found in [9]–[11]. Hamzaoui in [12] provided a good survey for Joint Source Channel Coding (JSCC)-FEC based UEP schemes to optimize reconstructed image quality with delay deadline constraint over wireless channels. In [13] Wu proposed a scalable JSCC scheme to achieve optimized overall distortion reduction for multiple reconstructed images. In that approach, the layered distortion expectation was modeled and a quality scalable image coder was used to optimally allocate bit budget among all sources. In [14] a JSCC scheme tailored for JPEG2000 was presented to minimize the end to end distortion within a total transmission rate constraint over memory-less channels. The UEP was provided via combining PHY FEC and JPEG2000 error detection and localization functionality. Multiple Description Coding (MDC) with FEC based UEP works fine with low delay real-time packet loss recovery techniques such as those shown in [15]–[17] for delay sensitive multimedia delivery applications. But the path diversity based error protections in those approaches need to continuously monitor path quality on each hop and report this to source coding nodes [18], and the overhead of which makes it impossible to be utilized in low cost and energy constrained WMSNs. In [18] Wu proposed an FEC based UEP approach for energy efficient image transmission in WMSN, and studied the energy-quality tradeoff. In that approach, the wireless channel was modeled using a two

TABLE I
SUMMARY OF THE KEY NOTATIONS USED IN THE EQUATIONS

Symbol	Definition
N	Total number of bit-planes in the compressed bit stream
$\Delta_p(j)$, $\Delta_v(j)$	The distortion reduction for the p-data segment and v-date segment in the $j-th$ bit-plane
$\varepsilon[\Delta]$	Expectation of the total distortion reduction
$\varepsilon[E]$	Expectation of the total energy consumption for transmitting the whole image
$E_{\max}$	The energy budget of transmitting the whole image
η	Resource allocation strategy for each segment
ρ	Packet loss ratio of transmitting a single segment
$\overline{E}$	Energy consumption of transmitting a single segment
e	Desirable BER of transmitting a segment
m, $\overline{m}$	Link layer ARQ retry limit and average number of retransmissions
R_s , N_0 , b, A	Physical layer symbol rate, noise power density, modulation constellation size, and channel state information.
R, R_o	Physical layer transmission data rate for data packets and control overhead packets
L_r , L_c , L_a , L	Lengths of RTS, CTS, ACK and DATA packets
E_r , E_c , E_d , E_a , E_s	The energy cost of transmitting RTS, CTS, DATA, ACK packets, and the average energy consumption of a successful link layer four-way handshaking.
P_t , P_r , $P_{\max}$	Transmission power and receive power for transferring DATA packets, and the maximum power used for transmitting control packets

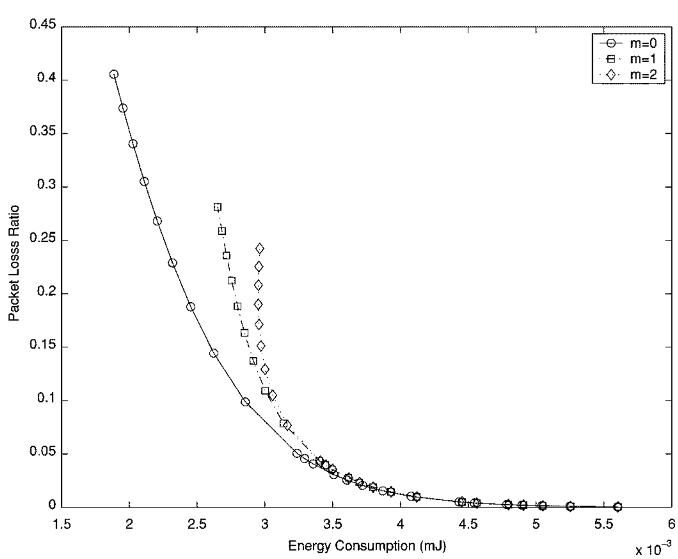

Fig. 2. Energy-quality performance of delivering packet with 36 bytes and channel state factor -90 dB, using QPSK modulation.

state Markov model, and Reed-Solomon coding was used for FEC. However, all aforementioned works took layered UEP approach without considering the important differences among intra-image position and value information.

To sum up, existing UEP schemes are mostly targeted for (1) delay constrained distortion reduction optimization without consideration of energy resources in WMSN, and (2) layer oriented optimization without considering position-value diversity in the image bit stream. Unfortunately, the approaches for delay constrained distortion minimization can not be directly applied to WMSN due to the high priority of energy efficiency, and the quality gain of the layer based UEP schemes is very limited. The preliminary work of this paper has been presented in [19], in which we showed the potential of achieving energy efficiency and image quality simultaneously by considering image position-value diversity. In this paper we propose a new position oriented resource allocation scheme for image transmission applications over WMSNs, to provide the best effort image quality with strict energy budget constraint, which differs fundamentally from the traditional layered UEP approaches.

III. CROSS LAYER PROBLEM FORMULATION

A. Bit Stream Separation

Position information denoting the bit stream structures is more sensitive to bit errors and packet loss than value information especially in an error prone wireless channel, because the decoding of value information depends on the successful decoding of position information. Wavelet based compression algorithms organize the structural information and value information in different coding passes, and position information and value information can be desirably separated via coding pass partition. Algorithm 1 shows how to identify position and value information from standard wavelet codec such as those given in [2], [34].

Coding pass partition for significant positions and insignificant values

1: Initialize p-data segment buffers $pBuf$ to store position information, and v-data segment buffers $vBuf$ to store value information. Perform wavelet transform on the original image. The wavelet coefficients are stored in Matrix X, with x rows and y columns.
2: Identify the initial magnitude quantization threshold T for iterative bit-plane coding loops. The initial threshold is determined by $T = 2^{\log_2(\max(|X(i,j)|))}$, where $0 \leq i \leq x-1$ and $0 \leq j \leq y-1$ [2]–[4]. Determine the maximum number of bit-planes N according to user defined compression ratio or rate-distortion requirement.
3: For bit-plane iteration $\gamma = 0$ to $N-1$, do the following steps (4–6):
4: Perform coding pass of significant position information. Scan the wavelet coefficients in X according to Morton scanning order. Given the reference quantization threshold T used in the current bit-plane, a coefficient can be determined explicitly as either a large-magnitude coefficient (magnitude is larger than T) or a small-magnitude coefficient (magnitude is smaller than T). As described in Section I and the depiction in Fig. 1, the clustering models of the small-magnitude coefficients determine the locations of the large-magnitude coefficients.

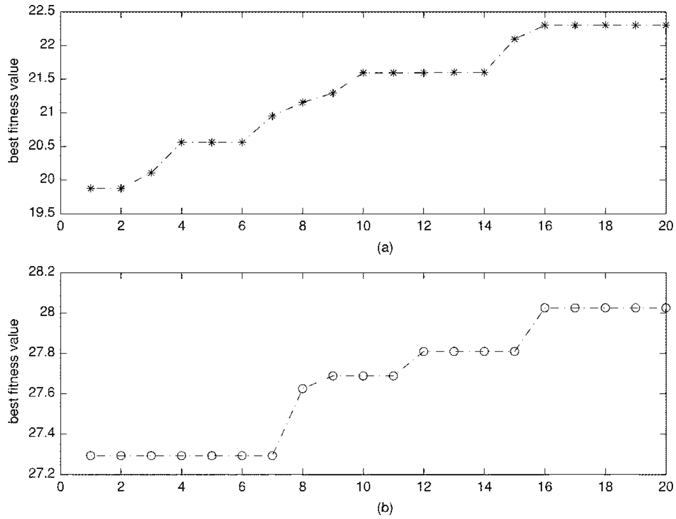

Fig. 3. Performance of genetic based evolution algorithm: (a) without grouping p-data segments and v-data segments; (b) with grouping p-data segments and v-data segments.

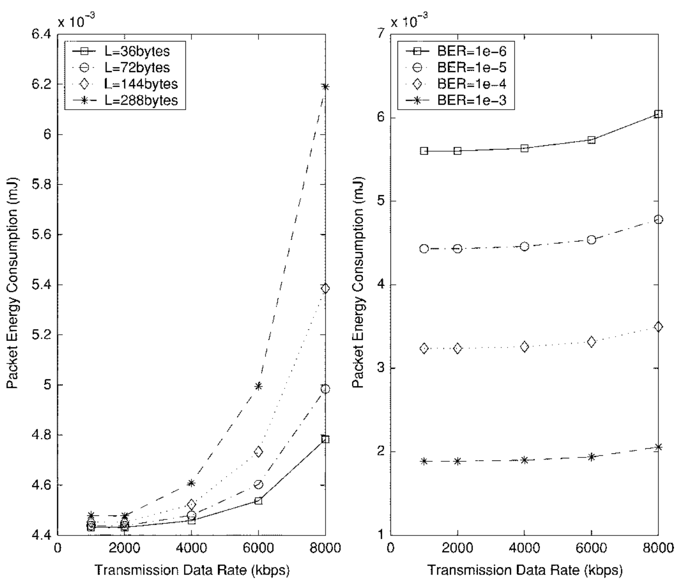

Fig. 4. Energy consumption of different transmission data rates for different segment lengths and desirable BER values, the channel state factor is -90 dB.

If a coefficient is determined as a large-magnitude coefficient, it is then coded as positive or negative significant symbol (according to its sign bit) to mark its location. Magnitude refinement coding pass will be further applied to it as described in Step 5. If a coefficient is determined as a small-magnitude coefficient (i.e., a bit "0" in the current bit-plane), it is coded as tree structure symbols. Specifically, it is encoded as a tree root symbol if all its wavelet coefficient matrix descendants in the same special direction are small-magnitude coefficients with regards to T. If one or more descendants are determined as large-magnitude coefficients regarding T, then this coefficient is encoded as an isolated zero symbol. The positive or negative significant symbols, isolated zeros and tree roots are stored as the p-data segment in $pBuf(\gamma)$ for the current bit-plane.

5: Perform coding pass of magnitude refinement for large-magnitude coefficients. All the coefficients marked as positive or negative symbols are further processed in this step to fine-tune the magnitude approximation. The most significant bit (MSB) in the current iteration denotes the magnitude of each positive or negative significant symbol and is stored as the v-data segment $vBuf(\gamma)$ in the current bit-plane. Till now the p-data segment and v-data segment for current bit-plane is formed.

6: Decrease the threshold by half $T = T/2$, go back to Step 3 for the next bit-plane. p-data segments and v-data segments in the following bit-planes are formed in the same way iteratively and progressively.

7: Output the image bit stream stored in $pBuf$ and $vBuf$ bit-plane by bit-plane in an embedded manner.

After compression, the bit stream is composed of embedded interleaving p-data and v-data segments in a decreasing importance order. Because bit stream structures are stored in p-data segments, incorrect symbols in p-data segments cause next-bit-plane bits misinterpreted, while incorrect bits in v-data segments do not. Fig. 1 also shows the reconstructed images with different p-data segments and v-data segments erased in different bit-planes. It is clear that significant noise is incurred perceptually when p-data segment is missing even in a high-level refinement bit-plane. On the contrary, even though v-data segment in low bit-plane is erased, the reconstructed image can still convey most information in the original image. This is because of the dependency between p-data and v-data segments. The correct decoding of p-data segment depends on the correct decoding of previous p-data segments only, but the correct decoding of v-data segment depends on previous bit-planes of both v-data and p-data segments.

Although we take tree based compression algorithms such as those given in [2], [34] as examples in this paper, the proposed position oriented UEP scheme is general and it is independent of the specific wavelet compression algorithms. The reason of selecting the tree based algorithms as the baseline is that position and value information can be easily separated during the partition process as described in Algorithm 1. The proposed scheme can be easily extended to other wavelet based image compression algorithms such as EBCOT [4] based JPEG2000, because essential position-value diversity is the spatial inheritance of digital image itself and the clusters of small-magnitude wavelet coefficients (i.e., the location information of the large-magnitude coefficients) can be efficiently represented as the clean-up passes, context formation models and arithmetic codes. As long as the image compression algorithms can extract position information and value information in the output streams, they can be easily and seamlessly applied to the proposed position oriented UEP framework.

B. Problem Formulation

Our cross layer resource allocation problem for image transmission in sensor networks can be formulated as an energy-constrained quality maximization problem. Let N be the total number of bit-planes in the embedded bit stream, $\Delta_p(j)$ and $\Delta_v(j)$ denote the distortion reduction (i.e., the amount by which the distortion of the received and reconstructed image will decrease with the successful decoding of the source bits contained in the segment) for the j-th p-data segment and the j-th v-data segment respectively. The distortion reduction of each segment can be measured by calculating the decoded image quality improvement in a way similar to [7], [9], [35], or estimated according to the wavelet coefficient square error units similar to [4], [36], [37]. Detailed discussion about generic distortion reduction acquisition and the application in cross layer optimization can be referred from these recent studies. $\rho_p(j)$ and $\rho_v(j)$ denote the corresponding loss ratio of the j-th p-data and v-data segment respectively. Let $\varepsilon[\cdot]$ denote the mathematical expectation. $\varepsilon[\Delta]$ is the expectation of total distortion reduction, which can be expressed as follows:

$$\varepsilon[\Delta] = \sum_{i=0}^{N-1}\left\{\left(\sum_{j=0}^{i}\Delta_p(j)\right)\prod_{j=0}^{i}(1-\rho_p(j)) + \left(\sum_{j=0}^{i}\Delta_v(j)\right)\prod_{j=0}^{i}(1 -\rho_p(j))\prod_{j=0}^{i}(1-\rho_v(j))\right\}\rho_p(i+1). \quad (1)$$

The distortion reduction expectation of p-data segments in (1) is expressed in a way similar to [13]. The layered dependency in that study is similar to the p-data segment dependency here, and $\rho_p(i+1) = 1$ denotes the end of embedded bit stream. In (1), the expected distortion reductions of p-data segments are expressed as the summation of the weight $\sum_{j=0}^{i}\Delta_p(j)$ with the corresponding probability $\prod_{j=0}^{i}(1-\rho_p(j))$ for successful decoding of each p-data segment. Distortion reduction expectation of all v-data segments is a little bit different. Each v-data segment depends on all p-data segments in previous and current bit-planes, as well as all v-data segments in previous bit-planes. Thus the distortion reduction expectation of v-data segments part can be expressed as the summation of the weight $\sum_{j=0}^{i}\Delta_v(j)$ and the probability $\prod_{j=0}^{i}(1-\rho_p(j))\prod_{j=0}^{i}(1-\rho_v(j))$ of each v-data segment successful decoding event. Equation (1) gives the close form expression of the expected distortion reduction, which is the objective function of the proposed optimization algorithm. Here we can roughly see that without p-data segments, v-data segments can hardly make any contribution to image reconstruction.

Now we derive the energy constraint function. Let $\varepsilon[E]$ denote the energy consumption expectation of delivering the whole image bit stream. Also let $\overline{E}_p(i)$ and $\overline{E}_v(i)$ denote the average energy consumption of delivering the p-data segment and v-data segment in the i-th bit-plane respectively. The total energy consumption of delivering the whole image bit stream can be expressed in the following equation:

$$\varepsilon[E] = \sum_{i=0}^{N-1}\{\overline{E}_p(i) + \overline{E}_v(i)\}. \quad (2)$$

Let $\eta_p(i)$ and $\eta_v(i)$ denote the resource allocation strategies (including desirable BER e, ARQ retry limit m, and transmission data rate R, i.e., $\eta = \{e, m, R\}$) of the p-data segment and v-data segment in the i-th bit-plane respectively. The desirable BER has been widely used as an optimization parameter such as [30], [31], which can be physically translated into the optimal transmission power in a given channel condition. The resource allocation strategy η of each segment can fine tune the average loss ratio ρ and the average energy consumption $\overline{E}$ of that segment. Let $E_{\max}$ denote the energy budget for the whole image transmission. The optimization problem can be formulated as follows:

$$\{\eta_p(i), \eta_v(i)\}_{i\in\{0,1,2,\ldots,N-1\}} = \arg\max(\varepsilon[\Delta]) \quad (3)$$

subject to

$$\varepsilon[E] \le E_{\max} \quad (4)$$

In the following two sections we present details of how to solve the cross layer optimization problem.

It is worth noting that the energy budget for transmitting a single image is determined by the upper layer (i.e., network layer) scheduling. A practical WMSN framework involves energy constrained quality optimization on each link as well as the optimal energy distribution through the whole network. The major concerns on each link are energy efficiency and media quality, while those concerns are network lifetime and load balancing in network layer. The network lifetime relies heavily on the energy efficiency on each individual link, as well as the energy distribution on each routing path. In this paper we focus on how to achieve optimal image quality given an energy budget on each link, and this energy budget is assumed to be provided by network layer network lifetime maximization algorithms such as [32], [33].

IV. Energy-Quality-Resource Allocation Mapping for a Single Segment

In this section we establish the layer 2 energy-quality performance mapping: $\{\rho, \overline{E}\} \mapsto \eta = \{e, m, R\}$ for each single segment with length L. In the multirate WMSN platforms [20]–[22], average energy consumption and average loss ratio of transferring each segment is related to the desirable BER requirement e, ARQ retry limit m, and the scalable transmission data rate R. The following parameters are known as protocol specific parameters. L_r, L_c and L_a are the overhead packet lengths including RTS, CTS and ACK; $P_{\max}$ denotes the power required for transmitting overhead packets, P_r denotes the receive power; R_o denotes the transmission data rate of the overhead packets; l denotes the virtual packet length of the timeout event which can be easily calculated from the time out value T_o of receiving a packet $l = T_o \times R_o$. Although contention based protocols with RTS-CTS handshake is used as an example here, the energy-quality-resource allocation model is general and easy to be extended to other protocols in WMSN without RTS-CTS.

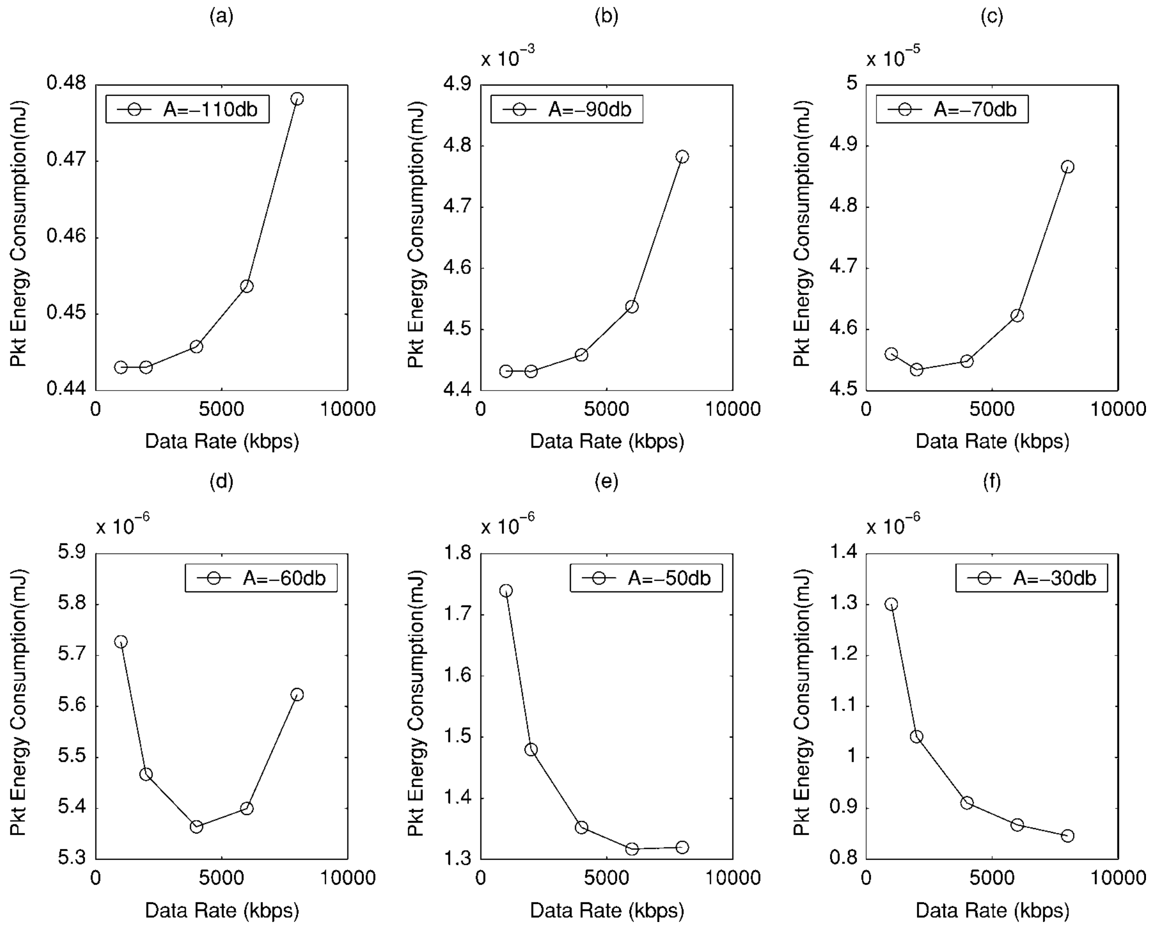

Fig. 5. Optimal transmission data rate in various channel conditions. Energy consumption is measured for a TinyOS packet delivered with desirable BER 1e-5.

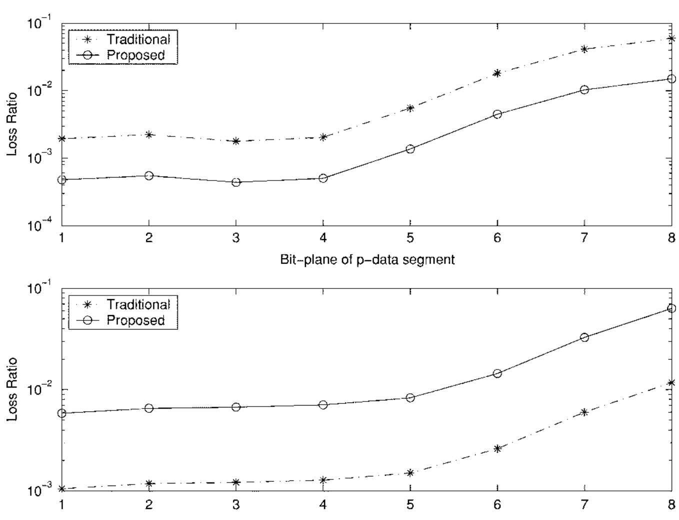

Fig. 6. Average loss ratio of different p-data segments and v-data segments, with compression ratio 1:0.3 and energy budget 0.08 mJ applied to both approaches.

A. Multirate Power Versatility

The desirable BER value e can be mapped to an optimal transmission power value P_t given the modulation scheme, constellation size b, frequency bandwidth R_s, noise power density N_0, and channel state information factor A according to [23]–[25]. For example, the optimal transmission power P_t can be expressed in terms of desirable BER e for BPSK and QPSK modulation schemes [23], [24] as

$$P_t = \frac{N_0 R_s b}{A}\{\mathrm{erfc}^{-1}(2e)\}^2. \tag{5}$$

And for M-QAM modulation scheme with $b \in \{2,4,6,8\}$, according to [24], [25] the optimal transmission power can be expressed as follows:

$$P_t = \frac{2N_0 R_s (2^b - 1)}{3A}\left\{erfc^{-1}\left(\frac{be}{2\left(1-\frac{1}{2^{\frac{b}{2}}}\right)}\right)\right\}^2. \tag{6}$$

We can evaluate the two equations by letting $b = 2$, and the two equations have the same form as that of QPSK modulation scheme. From these equations it is critical to see that the decrease of transmission data rate $R = R_s b$ (the transmission data rate of overhead packets is expressed as $R_o = R_s$, assuming basic BPSK modulation scheme is used for overhead packet transmission) is disproportionate to the decrease of transmission power. Transmitting data at a lower data rate with a more robust modulation scheme achieves much better power efficiency compared with the higher data rate transmission. This multirate

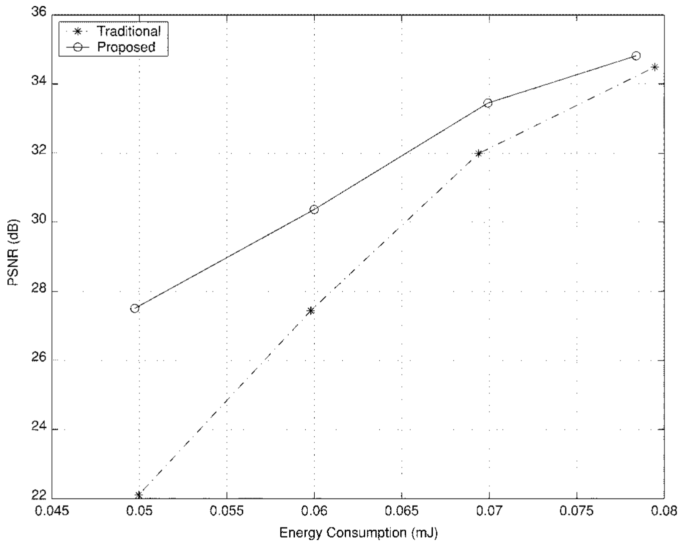

Fig. 7. PSNR versus energy consumption, compression ratio is 1:0.3.

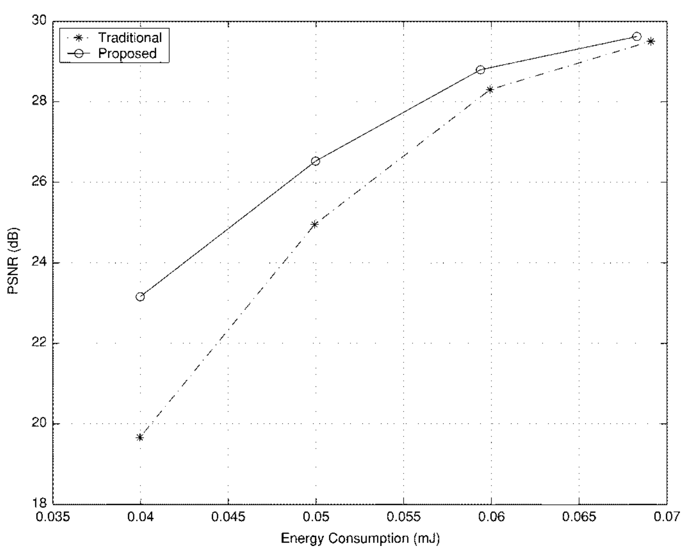

Fig. 8. PSNR versus energy consumption, compression ratio is 1:0.15.

power versatility provides significant potential to improve energy efficiency via multirate transmission.

B. Multirate Energy-Quality Optimality

In order to express the average loss ratio ρ and average energy consumption $\overline{E}$, here we define a fully ordered set $\Omega = \{r, c, d, a\}$, where the elements r, c, d and a denote the events of RTS, CTS, DATA, and ACK packet delivery failure. The set Ω is fully ordered $(r < c < d < a)$ because the delivery of CTS depends on the successful delivery of RTS packet, and the delivery of DATA depends on the successful delivery of CTS, and so on. Let e_o be the bit error rate of control overhead packets, e_o can be simply determined as $e_o = (1/2)\mathrm{erfc}(\sqrt{(P_{\max}A/R_s bN_0)})$ according to (5) given the protocol specified $P_{\max}$. Let p_i denote the packet error probability of the i-th packet in Ω. The packet loss probability for overhead packets including RTS, CTS and

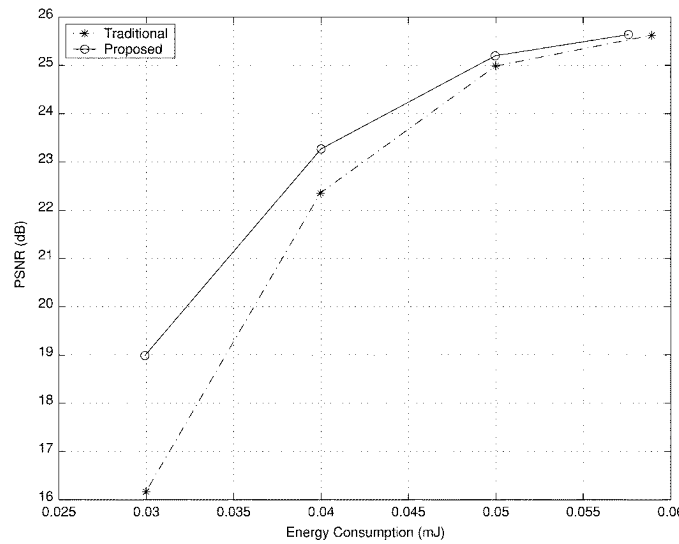

Fig. 9. PSNR versus energy consumption, compression ratio is 1:0.05.

ACK can be written as:

$$p_i = \prod_{k\in\Omega, k<i} (1 - p_k) \times \{1 - (1 - e_o)^{L_k}\}, \quad \forall i \in \Omega, \quad i \neq d. \tag{7}$$

For example, the packet error probability of RTS packet failure can be easily expressed as $p_r = 1 - (1 - e_o)^{L_r}$. Let e be the desirable BER for DATA packet with length L. The DATA packet delivery error probability becomes

$$p_i = \prod_{k\in\{r,c\}} (1 - p_k) \times \{1 - (1 - e)^{L}\}, \quad i \in \Omega, \quad i = d. \tag{8}$$

The corresponding energy cost due to RTS packet delivery failure is

$$E_r = (P_{\max} + P_r)\frac{L_r}{R_o} + P_r(\frac{L_c + 2l}{R_o})). \tag{9}$$

In the similar way, the energy cost due to CTS packet failure is expressed as

$$E_c = (P_{\max} + P_r)\frac{L_r + L_c}{R_o} + P_r\frac{L + 2l}{R_o}. \tag{10}$$

The DATA packets are transmitted using the scaled transmission rate R and optimally controlled power P_t. The energy cost due to DATA packet failure is

$$E_d = (P_{\max} + P_r)\frac{L_r + L_c}{R_o} + (P_t + P_r)\frac{L}{R} + P_r\left(\frac{L_a + 2l}{R_o}\right). \tag{11}$$

Similarly, the energy cost due to ACK packet failure becomes

$$E_a = (P_{\max} + P_r)\frac{L_r + L_c + L_a}{R_o} + (P_t + P_r)\frac{L}{R} + P_r\frac{l}{R_o}. \tag{12}$$

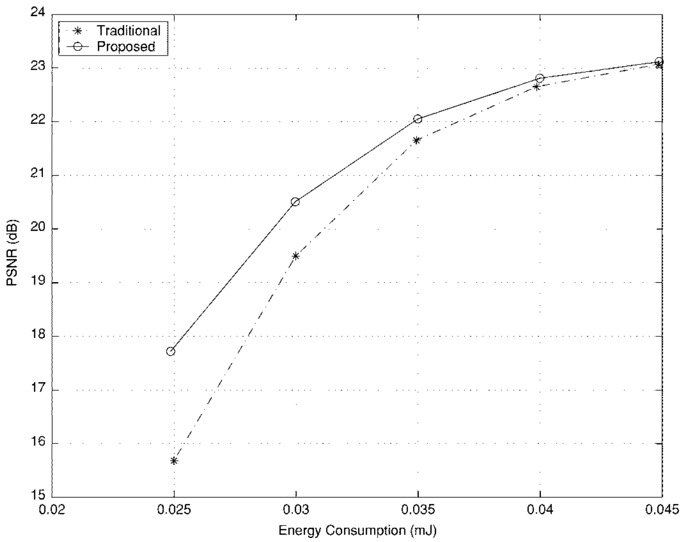

Fig. 10. PSNR versus energy consumption, compression ratio is 1:0.02.

On the other hand, the energy cost of sending a packet successfully is expressed as:

$$E_s = (P_{\max} + P_r)\frac{L_r + L_c + L_a}{R_o} + (P_t + P_r)\frac{L}{R}. \tag{13}$$

Based on the four way hand shake nature, the probability of packet delivery failure p without retry can be expressed as $p = \sum_{i\in\Omega} p_i$. Let m denote the ARQ retry limit, according to [6] the average retransmission count $\overline{m}$ can be expressed as a function of p and m, or

$$\overline{m} = (1-p)\sum_{i=1}^{m} i \times p^{i-1} + (m+1)p^m. \tag{14}$$

Then we can easily approximate the average loss ratio ρ, which is actually a function of desirable BER e and ARQ retry limit m, as

$$\rho = 1 - (1-p) \times \sum_{i=1}^{\overline{m}} p^{i-1}. \tag{15}$$

The average energy consumption $\overline{E}$, which is a function of desirable BER e, ARQ retry limit m, and transmission data rate R, can be expressed in the following equation:

$$\overline{E} = \overline{m} \times \left\{ \sum_{i\in\Omega} p_i E_i + \left(1 - \sum_{i\in\Omega} p_i\right) E_s \right\}. \tag{16}$$

V. Simplification of Cross Layer Optimization Problem

In (3) and (4), network parameters (i.e., desirable BER e, ARQ retry limit m, and transmission data rate R) are allocated to each p-data or v-data segment to achieve optimal image quality. This allocation must follow the energy budget requirement. However, the optimization for a large solution space is time and resource consuming in WMSN for real time image delivery applications. We practically design a specific evolution algorithm to reduce the number of optimization parameters. The optimization problem is simplified and solved in three steps. First, the transmission data rate is optimized independently of the evolution algorithm. Secondly, desirable BER is selected as a significant parameter over ARQ retry limit. Finally, the p-data segments and v-data segments are efficiently grouped which significantly reduces optimization complexity.

A. Independent Transmission Data Rate Optimization

In this paper we apply optimal power control to the radio module as described in Section IV Part A, which makes transmission rate R (or the modulation constellation size b) independent of the packet loss ratio ρ. This independency can be verified from (15) and the related equations because either the transmission data rate R or the modulation constellation size b is not a variable in calculating the average loss ratio ρ. Thus R is independent of the total expected distortion reduction expressed in (1), and the transmission rate optimization can be performed separately. Although transmission rate optimization needs desirable BER e, ARQ retry limit m and segment length L as input parameters, optimal transmission rate is dominantly determined by channel state factor A according to our extensive simulation studies. On the other hand, the available choices of PHY layer modulation schemes are limited and enumerable [5]. Thus available transmission rates are discrete and enumerable, too. In this paper we only have five available discrete transmission data rates. The optimal transmission rate in terms of minimal normalized energy consumption (energy consumption per information bit of pure data) including protocol overhead can be acquired by a simple enumeration search among the five data rates for a given value of A. This simple enumeration can be easily handled in a low cost radio module. Similar modulation enumeration approaches are also found in latest researches such as [5] and [31]. With the assumption that multiple modulation schemes are provided by the radio module, the proposed transmission data optimization can achieve significant energy efficiency gain with little computational overhead. The resource allocation strategy η in (3) is simplified as $\eta = \{e, m\}$. The rate optimization is very easy to be integrated into MAC protocols, leaving the duty cycle management and channel access functionalities untouched, as shown in Algorithm 2.

Coupling rate optimization with MAC implementation

```
/*Initialize and hook the SendData event */
RegisterCallbackFunction(SendData, OnDataSend);
/*Wait until there is a chance to send data */
WaitforDataTransmissionOpportunity();
/*This function is called automatically when there is a data
transmission opportunity.*/
void MAC::OnDataSend()
{
    /*Setup the configuration of this packet*/
```

$A =$ call GetInstantaneousChannelInformation();

$e =$ call GetOptimizedTransmissionParameters();

$R =$ call GetOptimizedTrasmissionRate(A);

*/*Choose proper modulation scheme:*/*

call PhyRadioCtrl.SetTransmissionRate(R);

$P_t =$ GetOptimizedTransmissionPower(A, e, R);

call PhyRadioCtrl.PowerSupply(P_t);

*/*m_pTxBuf stores the data to be sent out*/*

setupPkt(m_pTxBuf, R, P_t);

*/*Hereby start real transmission*/*

$\mathrm{state} = \mathrm{TX\_PKT}$;

call PhyComm.txPkt(m_pTxBuf);

}

B. Significant Parameter Selection

Desirable BER e can be translated into optimal transmission power P_t in PHY layer, which is a continuous function desirable for fine-tuning the layer 2 $\{\rho, \overline{E}\}$ performance. Although higher ARQ retry limit m can reduce the average loss ratio ρ significantly, the retransmission overhead incurs considerable energy penalty. Furthermore, ARQ retry limit m is discrete, which is undesirable to fine-tune the $\{\rho, \overline{E}\}$ performance. The $\{\rho, \overline{E}\}$ performance of delivering a TinyOS [26] packet is shown in Fig. 2. It is clear that the desirable BER e is the significant parameter and the ARQ retry limit m is an insignificant parameter for controlling the $\{\rho, \overline{E}\}$ performance. The curve $m = 0$ is approximate to the $\{\rho, \overline{E}\}$ convex hull, meaning that the most efficient resource allocation can be achieved through fine-tuning e itself. The resource allocation strategies η in (3) is further simplified as $\eta = \{e\}$ for each segment through significant parameter selection.

In a practical environment such as the TinyOS platform, transmission power control is typically performed by writing an 8-bit register using NesC code, for example, *PotC.setPot(uint8_t nTxPower)*. The valid range of transmission power is [0,99] for the Micaz platform. Then controlling the transmission power in a practical environment becomes very simple: get the desirable BER value e from the output of Algorithm 3 as described later, and translate the desirable BER e into the optimal transmission power P_t according to (5) and (6), and then normalize P_t in the range of [0,99] according to the minimum and maximum power supported by the radio module, and finally supply the radio with the normalized power.

C. Grouping Position and Value Segments in Evolution Algorithm

Although independent transmission data rate optimization and significant parameter selection reduce the optimization complexity considerably, it is still impractical to assign resource allocation strategy η to each segment. Grouping all the p-data segments into one group and v-data segments into another group can efficiently reduce the complexity. Assigning one desirable BER e to each group naturally produces a hierarchical layer based UEP across all the bit-planes, because the segment size in image bit stream is almost naturally increasing with bit-planes. Segments in higher bit-planes have higher ρ values while segments in lower bit-planes have lower ρ values. Then the UEP between p-data segments and v-data segments, as well as the UEP between different bit-planes are jointly simplified as a two-element resource allocation vector $\{e_p, e_v\}$. By this non-trivial approximation, the genetic based evolution algorithm can be designed as Algorithm 3, and in the worst case, the complexity is $O(n^2)$. The complexity without such simplification or approximation is $O(n^{6N})$, because there are N bit-planes and 6 parameters ($\{e, m, R\}$ for each p-data segment and v-segment) in each bit-plane needed to be optimized. Fig. 3 shows the effectiveness of grouping p-data segments and v-data segments. In Fig. 3(a), each segment is assigned with a desirable BER for an 8 bit-plane bit stream, thus a total of 16 parameters need to be optimized. Although there is more than 2 dB distortion reduction improvement in 20 generations, the best fitness value after 20 generations is still very low. In Fig. 3(b) the p-data segment group and v-data segment each have a desirable BER assignment, and only 2 parameters need to be optimized. This shows the effectiveness of position and value segment grouping.

Genetic based evolution for maximum distortion reduction with energy constraint.

1. Define the algorithm I/O:

   Input: image distortion reduction Δ_v and Δ_v of each p-data and v-data segment, length L of each segment, channel state factor A and energy budget $E_{\max}$.

   Output: optimal resource allocation vector $\{e_p, e_v\}$.

2. Binary coding and decoding for each chromosome: each possible solution $\{e_p, e_v\}$ is coded as a chromosome and each element e_p and e_v in the chromosome is coded as a gene.

   Perform $e = e/1000$ for each gene to make desirable BER more effective. Initialize the size S_{pop} of population and the maximal evolution iterations or generations G_{itr}.

   Create the first generation randomly as $\{\{e_p(0,0), e_v(0,0), \ldots \{e_p(0, S_{\mathrm{pop}}-1), e_v(0, S_{\mathrm{pop}}-1)\}\}$.

3. For iteration $\gamma = 0$ to $G_{\mathrm{itr}} - 1$, do the following steps (4–6) for evolution.

4. Evaluate the fitness of each chromosome in the current generation γ.

   Let ζ denote a small positive constant value to make the energy budget threshold slightly higher than $E_{\max}$, which makes the fitness evaluation more effective.

   Let $u(\cdot)$ denote the step function.

   For $i = 0; i \leq S_{\mathrm{pop}} - 1; i++$ do

Calculate the total energy consumption expectation $\varepsilon[E(i)]$ and the expected distortion reduction $\varepsilon[\Delta(i)]$, using the current $\{e_p(\gamma, i), e_v(\gamma, i)\}$.

The fitness f of each chromosome can be evaluated using $f(i) = \varepsilon[\Delta(i)] \times u(E_{\max} - \varepsilon[E(i)] + \zeta)$.

End for.

5. In the current generation γ, sort the chromosome in descending order according to the fitness values f.

6. Crossover of elitism parents in the current population.

For $i = 0; i \leq S_{\text{pop}} - 1; i++$ do

Calculate the probability that one chromosome crossover with others using $p_{\text{cross}}(i) = (f(i))/(\sum_{k=0}^{S_{\text{pop}}} f(k))$;

End for.

Randomly crossover chromosomes $\{e_p(\gamma, i), e_v(\gamma, i)\}$ with weight $p_{\text{cross}}(i)$, to produce a new generation of population

$$\{\{e_p(\gamma+1, 0), e_v(\gamma+1, 0)\}, \ldots$$
$$\{e_p(\gamma+1, S_{\text{pop}}-1), e_v(\gamma+1, S_{\text{pop}}-1)\}\}$$

with the same population size S_{pop}. Go to Step 3 to evaluate the loop condition.

7. Output the best chromosome in the current population with the largest f value, while the energy consumption is within the budget constraint $E_{\max}$.

The computational complexity of the proposed approach before p-data and v-data segment grouping is directly related to the number of image segments. The compressed bit stream is composed of p-data segment and v-data segment decoding units, and each segment is further fragmented into multiple packets during transmission. The number of segments in the compressed bit stream is related to the number of bit-plane layers, which controls the compression ratio and image quality tradeoff. With the proposed p-data and v-data segment grouping described in this subsection, the computational complexity is further reduced to a two parameter optimization problem. In a practical setting of WMSN, such as Cyclops+Micaz sensor networks, the image resolution is low due to the hardware size and capability (64×64 pixels in a monochrome picture, and each pixel is 8 bits length) and the packet length is short for combating transmission errors in wireless channels (36 bytes for a standard TinyOS packet). Thus with this practical setting, totally 144 packets will be created without compression. With a typical compression 1:0.3 (raw image size: compressed bit stream length) applied to this raw image, totally 35 packets in 8 bit-planes are created for transmission. These 35 packets in the 8 bit-planes are grouped into 16 image segments by Algorithm 1 (8 p-data segments and 8 v-data segments, each segment contains multiple packets). Thus the complexity before p-data and v-data segment grouping is to find the optimal transmission strategies for these 16 segments, where the number of segments is much smaller than the number of packets. The proposed approach is further simplified by grouping the p-data segments and v-data segments into two types, and transmission strategies are optimized for these two types. Thus, only two parameters need to be optimized regardless of the image size and packet size, and the proposed approach is light weighted in WMSN.

VI. Simulation

In this section, we evaluate the energy-quality gain of the proposed position oriented resource allocation scheme. We employ T-MAC [27] as the baseline MAC protocol and with multirate enhancement [21] applied. For T-MAC data packet [28] in TinyOS [26], the MAC header is 11 bytes and the pure payload is 36 bytes. For the overhead packet such as ACK, the length is 13 bytes; RTS and CTS packets are both 15 bytes [21]. The virtual packet length l for timeout event in T-MAC is selected the same as one RTS packet length. The preamble length is 18 bytes [29] and the receive power is 0.001 mW. The default channel state factor A is -90 db. The noise power density value is 4×10^{-21} J/Hz. Symbol rate is 1000 kHz, and BPSK, QPSK and M-QAM modulation schemes with even constellation sizes are used in simulation.

A. Independent Transmission Data Rate Optimization

The simulation results of transmission data rate optimization show two positive effects. First, the optimal transmission data rate is not sensitive to the desirable BER e or the segment length L, but very sensitive to channel state factor A. Furthermore, the optimized transmission data rate can achieve significant energy efficiency gain. The results in Figs. 4 and 5 validate the transmission rate optimization design in the previous section which takes A rather than e or L as input parameter. In Fig. 4, although e or L changes significantly, the optimal transmission data rate leading to the lowest energy consumption is always the one based on QPSK modulation scheme. This is because the channel state factor A remains the same, which is dominant in determining the optimal transmission data rate. The desirable BER and segment length are weak constraint parameters for optimizing transmission data rate.

However, the optimal transmission data rate is very sensitive to A, which is illustrated in Fig. 5. In relative harsh channel conditions, such as Fig. 5(a)–(c), lower rate transmissions achieve less normalized energy consumption; in relative good channel conditions such as Fig. 5(d)–(f), higher rate transmissions are favorable. Fig. 5 also shows the optimal transmission data rate achieves significant energy efficiency gain compared with other non-optimized transmission data rates in various channel conditions. For example, given the channel state factor -60 dB, the worst case transmission rate incurs 5.7271e-5 mJ energy consumption and the sub-optimal leads to 5.3999e-5 mJ energy consumption, while the optimal transmission rate achieves 5.3641e-5 mJ energy consumption. Let $\beta = E_{\text{ref}}/E_{\text{opt}} - 1$ denote the energy efficiency improvement, where E_{opt} and E_{ref} are the energy consumption achieved by using the optimized transmission data rate and referenced transmission data rate respectively. In this channel condition, the optimized transmission date rate achieves 6.7% and 0.67% energy efficiency improvement with regards to the worst case and the sub-optimal case.

B. Position Oriented Resource Allocation With Energy Budget Constraint

In this part of simulation, the performance of the proposed position oriented resource allocation is shown and compared with traditional layer based UEP approaches. The results show by exploring the position and value diversity, the Peak Signal Noise Ratio (PSNR) can be significantly improved within the same energy budget. The image shown in Fig. 1 with 128×128 pixels and 8 bit per pixel is used as an example in the simulation. The energy-quality performance is also studied based on image bit streams with various compression ratios (Raw data length : compressed data length). To be fair, both approaches apply the transmission rate optimization independently, which has shown considerable energy efficiency gain in the last sub-section.

By applying the position oriented resource allocation scheme, p-data segments are effectively protected to enhance image quality while v-data segments are less protected to improve energy efficiency. Fig. 6 shows the average loss ratios of all p-data segments and v-data segments with 1:0.3 compression ratio and 0.08 mJ energy budget constraint. It is clear that, by applying the proposed cross layer optimization, loss ratios of p-data segments containing bit stream structure and position information are reduced, and the loss ratios of v-data segments containing magnitude value information are increased, compared with traditional layer based UEP approaches. The energy consumption penalty of more protection on important p-data segments is fully compensated by the less protection on those unimportant v-data segments. However, the distortion reduction is enhanced considerably. Similar results are obtained for other scenarios with different compression ratios and energy budget constraints.

The proposed approach not only explores UEP among different bit-planes, but also explores UEP between p-data and v-data segments in the same bit-plane. Figs. 7 to 10 illustrate the proposed scheme can achieve significantly improved distortion reduction and energy efficiency simultaneously, compared with traditional layer based approaches. Drawing a horizontal line in these figures, we can see that to achieve the same PSNR, the proposed approach consumes less energy. With the same energy consumption, the proposed approach can achieve higher distortion reduction. The reason is that in traditional layered UEP, the difference between p-data segments and v-data segments is not considered. These results strongly support the position oriented resource allocation, because the p-data segments of higher importance deserve more network resources allocation than less important v-data segments. The distortion penalty due to losing some of these v-data segments are effectively compensated by putting more effort on p-data segments.

Furthermore, the proposed position oriented resource allocation scheme is especially favorable for strict energy budget constraints (i.e., low energy consumption, or scarce network resources) and lower compression ratios. For example in Fig. 7, the distortion reductions are very close for both approaches with 0.08 mJ energy budget constraint; with 0.05 mJ energy budget constraint, the proposed approach can achieve around 5 dB distortion reduction gain over traditional approaches. The reason is that with strict energy budget constraints, the proposed approach can allocate the scarce resources on position information other than magnitude value information. As illustrated in Figs. 7 to 10, the distortion reduction gains for the strictest energy budget constraints decrease when the compression ratios increase. This is because less magnitude value information and more position information are produced for image bit streams with higher compression ratios. Position oriented resource allocation becomes more efficient with lower compression ratios and less efficient with higher compression ratios.

VII. Conclusion

In this paper, we have proposed a position based cross layer resource allocation approach to achieve optimal image transmission quality while assuring energy efficiency in WMSNs. Specifically, the unequal importance among image-pixel-position information and image-pixel-value information is extensively studied, and the network resource allocation strategies are optimized across PHY, MAC and APP layers regarding p-data and v-data distortion reduction correlations. The important p-data segments containing structure and position information are more reliably protected and transmitted to improve image quality, and the relatively unimportant v-data segments containing image pixel value information are less protected during transmission to improve energy efficiency. Simulation results show that this proposed approach has increased the image transmission quality significantly with a performance gain around 3–5 dB, while still assuring energy efficiency especially with strict energy budget constraints and low image compression ratios.

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