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PERFORMANCE ANALYSIS FOR DCT-BASED CODED IMAGE COMMUNICATION IN WIRELESS MULTIMEDIA SENSOR NETWORKS

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Abstract- The objective of this paper is to study the image communication behavior of a wireless video sensor, and analyze its performance under resource constrained wireless multimedia sensor networks. Energy consumption and rate distortion model of DCT-based coded image compression and transmission is developed. Based on energy consumption and rate distortion model proposed, resource allocation is optimized with limited energy and bandwidth. Number of DCT coefficient and step size of quantization table is adapted according to the activity of monitoring scene, and then the energy consumption will be minimized. Simulations results are conducted to show the performance of our

work. The proposed scheme dramatically reduces image compression and transmission energy consumption under expected image distortion and transmission rate.

Index terms: Wireless multimedia sensor networks, image compression, image transmission, DCT.

I. INTRODUCTION

Wireless multimedia sensor networks (WMSN) consist of tiny camera nodes, which integrate the image sensor, embedded processor, and wireless transceiver. Because of its unique features of rapid deployment, flexibility, low maintenance cost, and robustness, WMSN have developed as a new technology with a number of potential applications, ranging from security to monitoring to telepresence [1]. The major task of WMSN is image communication, which is really a challenge for resource constraint wireless sensors.

The ultimate goal of image communication design for WMSN is to optimize the performance under limited resources. In traditional video communication applications, the major resource constraint is in the form of transmission bandwidth or storage space, which determines the output bit rate of a video encoder. Compared to traditional communication systems, WMSN operates under a set of unique resource constraints, including limited energy supply, on-board computational capability, and transmission bandwidth. Therefore, there is a need to extend the traditional R-D analysis by considering these new resource constraints in the WMSN. The objective of this study is to analyze the impact of resource constraints on the performance limit of a wireless video sensor.

Image communication is the dominant power-consuming operation in wireless video sensors over WMSN, which includes image compression and transmission. For the resource constraints in WMSN, the effect of image encoding is two-fold. First, efficient image compression significantly reduces the amount of the video data to be transmitted, which in turn saves a significant amount of energy in image transmission. Second, more efficient image compression often requires higher computational complexity and larger power consumption in computing. These two conflicting effects imply that in practical system design there is always a tradeoff among the bandwidth R, power consumption P, and video quality D. Therefore, to find the best trade-off solution, we need to develop an analytic framework to model the performance of the image communication in WMSN.

Image compression is lossy, which not only introduces distortion in the coded source in the form of quantization errors, but also makes the data stream highly sensitive to bit errors when transmitted over wireless channels [2]. Video distortion in wireless networks is mostly caused by lossy source coding, transmission errors originated by channel fading, buffer overflows and playout deadline misses. Since recharging for wireless video sensors is not practical, minimizing the energy consumption of wireless video sensors under resource constraints, which includes expected distortion of images and transmission rate, will be crucial. For image encoding on video sensor and streaming over WMSN, it is needed to analysis Rate-distortion (R-D) under energy constraints. In energy-aware image encoding, the coding distortion is not only a function of the encoding bit rate as in the traditional R-D analysis, but also a function of the power consumption.

Pudlewski et al. propose a rate control scheme based on both analytical and empirical models, along with a joint video and channel encoder rate allocation scheme [3]. The scheme jointly regulates the end-to-end data rate, the video quality, and the strength of the channel coding at the physical layer to minimize the distortion of the received video, and finds the combination of video and channel encoding that results in the best quality video at the receiver.

Zhihai He et al. analyze the P-R-D performance and develop an adaptive scheme to estimate the P-R-D model parameters and perform online energy optimization and control for real-time video compression [4].

Zhao Sun et al. develop an online complexity control and energy minimization scheme for real-time video encoding over portable devices [5]. They introduce a set of parameters to control the computational complexity and energy consumption of the video encoder. Based on neural network computations, the scheme determines the complexity control parameters to maximize the overall video encoding performance under energy constraints.

Zhenhua Tang et al. present an energy-minimized resource allocation scheme, which applies UEP of channel coding and UTPD jointly [6]. In this scheme, unequal transmission protections are adaptively assigned to various parts of compressed images according to their different sensitivities to transmission errors.

So far, existing methods and algorithms have been focused on encoder complexity and energy consumption reduction through heuristic adaptation or control instead of systematic energy optimization. This is because they lack an analytic model to characterize the optimum trade-off between energy consumption and encoding performance. In addition, even with existing energy saving technologies, the operational lifetime of portable video electronics still remains very short which has become one of the biggest impediments to our technology future. Therefore, it is important to develop new energy minimization approaches for WMSN.

In this work, we focus on energy consumption analysis and rate distortion analysis of image compression and image transmission in WMSN since these two consume a major portion of the total energy while the energy consumption of the remaining components depends on specific system design and is not easily controllable from an image compression perspective. Then a resource allocation optimization scheme is proposed according to the analysis.

II. ENERGY CONSUMPTION ANALYSIS

1. Energy Consumption of Image Compression

Typically, visual information needs to be compressed using one of the well known compression standards such as JPEG or JPEG2000 to save transmission bandwidth or storage space. Unfortunately, these standards are computational intensive and energy consuming. Since the limitations with respect to energy resources and on-board processing capability, we have to adapt a lightweight image compression algorithm to the requirement of WMSN [7]. The JPEG algorithm is utilized for the work presented here. While the JPEG2000 standard offers some significant advantages over the JPEG, it is much less widely deployed and also requires full-frame processing which can be challenging in light of memory limitations [8].

Typical video encoders, including video and image coding standards, such as MPEG-2, H.263, MPEG-4, and JPEG employ DCT encoding scheme. They have the following three major encoding modules: DCT, quantization, entropy encoding of the quantized DCT coefficients [9].

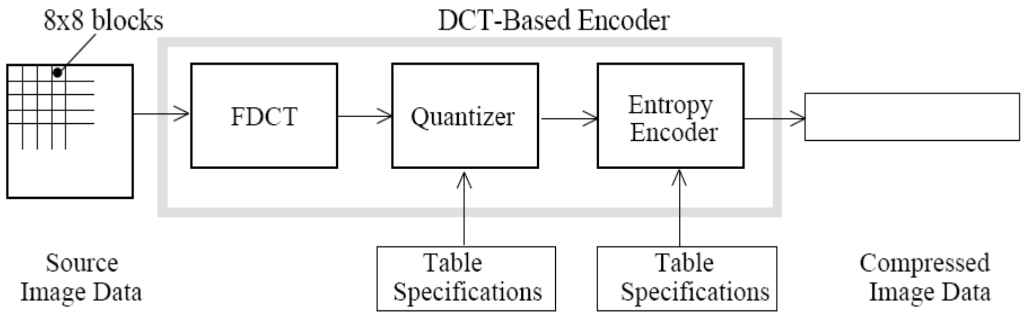

Figure 1. JPEG encoding

Let P_c be the required energy to compress the image data for JPEG stages. P_c can be formulated as follows:

$$P_c = P_{dct} + P_q + P_{entropy} \tag{1}$$

Where P_{dct}, P_q and $P_{entropy}$ represent the energies consumed at 2D DCT, quantization, and entropy coding stages, respectively.

At the encoder, source image samples are grouped into 8×8 blocks, shifted from unsigned integers with range $[0, 2^P - 1]$ to signed integers with range $[-2^{P-1}, 2^{P-1} - 1]$, and input to the Forward DCT (FDCT). At the decoder, the Inverse DCT (IDCT) outputs 8×8 sample blocks to form the reconstructed image. The following equations are the idealized mathematical definitions of the FDCT:

$$F(u,v) = \frac{1}{\sqrt{2k}} C(u)C(v)[\sum_{x=0}^{k-1}\sum_{y=0}^{k-1} f(x,y) * \cos\frac{(2x+1)u\pi}{2k}\cos\frac{(2x+1)v\pi}{2k}] \tag{2}$$

Where: $C(u),\ C(v) = 1/\sqrt{2}$ *for* $u, v = 0$;
$C(u),\ C(v) = 1$ *otherwise.*

Where u, v are the discrete frequency variables such that $0 \le u, v \le k-1$, k is the block size. $f(x,y)$ is the grey level of one pixel at (x, y) in the $N \times N$ image, where $0 \le x, y \le k-1$; $F(u,v)$ is the coefficient of the point (u,v). Each $k \times k$ block necessitates $k^2 \log_2 k$ multiplications and $3k^2 \log_2 k - 2k^2 + 2k$ additions for row-column method. Therefore the energy dissipated for one block is $(k^2 \log_2 k) p_{mult} + (3k^2 \log_2 k - 2k^2 + 2k) p_{add}$, where p_{mult} and p_{add} represent the energy consumption for multiplication and addition instructions. For an image of size $N \times N$ having $(\frac{N}{k})^2$ blocks, the total energy dissipated is:

$$P_{dct} = (\frac{N}{k})^2 p_{dct} = (N^2 \log_2 k) p_{mult} + (3N^2 \log_2 k - 2N^2 + \frac{2N^2}{k}) p_{add} \tag{3}$$

The processing energy by the quantization stage can be expressed as a function of $F(u,v)$ and $Q(u,v)$, where $Q(u,v)$ is a coefficient of the luminance quantization matrix Q defined for $k=8$, $0 \le u,v \le k-1$. Quantization is defined as division of each DCT coefficient by its corresponding quantizer step size, followed by rounding to the nearest integer:

$$F^Q(u,v) = Integer\ Round(\frac{F(u,v)}{Q(u,v)}) \tag{4}$$

Therefore, there are k^2 divisions and k^2 round operations per block and the energy dissipated is $p_q = k^2(p_{div} + p_r)$, where p_{div} and p_r are the energy consumed for division and round instructions, respectively. For one image $N \times N$, the total energy dissipated in this stage is:

$$P_q = (\frac{N}{k})^2 p_q = (\frac{N}{k})^2 k^2 (p_{div} + p_r) = N^2 (p_{div} + p_r) \tag{5}$$

After quantization, all of the quantized coefficients are ordered into the zigzag sequence. Zigzagging is a simple rearrangement of the $(k^2 - 1)$ AC coefficients ordered in a zigzagging way, from lower to higher frequencies. The zigzagging energy consumption on each block can be calculated as: $p_z = (k^2 - 1) p_{sh}$, where p_{sh} represents the energy consumption of the shift process. For one input image of size $N \times N$, where P_z represents the energy consumed at zigzagging stage, the total processing energy related to the zigzagging stage is:

$$P_z = (\frac{N}{k})^2 p_z = (\frac{N}{k})^2 (k^2 - 1) p_{sh} \tag{6}$$

Entropy coding can be considered as a 2 step process. The Baseline sequential codec uses run length encoding and Huffman coding for these 2 steps. Run length encoding of the $(k^2 - 1)$ AC coefficients is a rearrangement of the zigzagged sequence. It converts the zigzag sequence of quantized coefficients into an intermediate sequence of symbols. Huffman encoding converts the symbols to a data stream in which the symbols no longer have externally identifiable boundaries. Entropy coding can be formulated as follows:

$$P_{entropy} = P_{rle} + P_{huf} \tag{7}$$

Where P_{rle} and P_{huf} represent the energy consumed at RLE and Huffman encoding stages, respectively. Run length encoding of the AC coefficients can be interpreted mainly as a rearrangement of the zigzagged sequence. For Huffman encoding, the total energy dissipated per image for both DC and AC coefficients.

2. Energy Consumption of Image Transmission

The image transmission power is given by

$$P_t = c_t \cdot R_c = (\omega + \gamma d^n) \cdot R_c \tag{8}$$

Where c_t is the energy cost that is needed for successful transmission of one data bit. It depends on transmission distance and path loss index. R_c is the transmission bit rate, d is the transmission distance, n is the path-loss exponent, and γ is a model parameter related to encoding efficiency. Since the total power consumption P is fixed, and $P = P_c + P_t$, if we increase P_c, then decreases P_t. This implies that less bits can be transmitted because the transmission energy is proportional the number of bits to transmit. Therefore, image distortion increases.

III. RATE DISTORTION ANALYSIS

The major task of wireless video sensor is to compress image data and send the compressed bit stream to the aggregation and forwarding nodes (AFN). Its performance is measured by the quality of videos delivered to the AFN. Performance of image communication is measured by the quality of images delivered to the aggregation and forwarding nodes, which is commonly measured by the end-to-end distortion, denoted by D. It consists of two parts: image compression distortion and transmission distortion. The image compression distortion is caused by quantization errors during lossy video compression and is often measured by the mean squared error (MSE) between the original image and the encoder reconstruction, denoted by D_c. The transmission distortion is caused by transmission errors, such as packet loss, and is measured by the MSE between encoder reconstruction and decoded image at the receiver, denoted by D_t.

1. Image Compression Distortion

The image compression distortion is caused by lossy image compression and is often measured by the mean squared error between the original image and the encoder reconstruction, denoted by D_c [10]. The image compression bit rate R_c and distortion D_c can be considered as functions of ρ, which is the percentage of zeros among the quantized DCT coefficients. R_c and D_c are commonly treated as functions of the quantization step size q, and ρ monotonically increases wit q. Therefore, mathematically, R_c and D_c are also functions of ρ. The distortion model for image compression is given by:

$$D_c(\rho) = \sigma^2 e^{-\alpha(1-\rho)} \tag{9}$$

Where σ^2 is the variance of image data and α is a constant.

2. Image Transmission Distortion

In wireless video surveillance, wireless video sensor is allowed to retransmit the video packets if they are not received correctly. However, in WMSN monitoring, because of the stringent delay requirement, packet retransmissions are infeasible even if the packet is received with errors. These transmission errors will be passed to the decoder and cause decoding errors and error propagation to the subsequent frames.

In wireless image coding and transmission, channel coding is often used to correct bit errors in the coded video data stream. Increased error resilience often comes at the cost of higher bandwidth consumption. Due to the limited error correction capacity of the channel decoder, residual bit errors often still exist after error correction. When a corrupted codeword in the bit stream cannot be properly decoded, the video encoder will jump to the next packet starting with a resynchronization mark and skip all the intermediate bits. This introduces visible picture distortion at the receiver. Note that at the decoder the current reconstruction frame “corrupted” by bit errors may be used as the reference for the next frame. In this way, the channel distortion often severely degrades the video presentation quality.

The transmission distortion is caused by transmission errors, and is measured by the MSE between encoder reconstruction and decoded image at the receiver, denoted by D_t. In WMSN monitoring applications, because of the stringent delay requirement, packet retransmissions are infeasible even if the packet is received with errors. The video encoder will jump to the next packet and skip all the corrupted bits. The transmission errors will cause decoding errors and error propagation to the subsequent frames [11].

The average channel distortion caused by packet loss is proportional to the mean frame difference. Image transmission distortion caused by packet loss as packet retransmissions are infeasible, is given by

$$D_t = \frac{a}{1-b+b\xi} \cdot \frac{p}{1-p} \overline{F}_d(i) \tag{10}$$

Let p be the packet loss ratio and ξ be the average fraction of blocks in the image. a and b are model parameters, a is a constant that can be regarded as the energy loss ratio of the encoder filter, b is a constant that describing the object motion randomness of the monitoring scene. $F_d^c(i)$ represents the MSE between the current compressed frame and the previous frame, $F_d^c(i) = aF_d(i)$. $F_d(i)$ is the MSE between the current frame and the previous frame. $\overline{F}_d(i)$ is the average frame difference $F_d(i)$ of the total image sequence.

$$F_d(i) = \frac{1}{M \times N} \sum_{x=1,y=1}^{x=M,y=N} \left| f_i(x,y) - f_{i-1}(x,y) \right|^2 \tag{11}$$

IV. RESOURCE ALLOCATION OPTIMIZATION

Based on the analysis previously, energy consumption and rate-distortion of image compression and transmission can be optimized. In WMSN monitoring application, a video scene often experiences a series of events with time varying. Therefore, the data volume of each image frame to be encoded by wireless video sensor is often nonstationary. The encoder may treat the image sequences differently and performs optimum resource allocation among these images to minimize the overall encoding power consumption. To saving energy under resource constraints, encoder must be adapted to satisfy the actual situation in the monitoring scene.

In WMSN monitoring application, a video scene often experiences a series of events with time varying. Therefore, the data volume of each image frame to be encoded by wireless video sensor is often nonstationary. The encoder may treat the image sequences differently and be adapted to satisfy the actual situation in the monitoring scene to minimize the encoding power consumption [12]. Since the total power consumption P is fixed, and $P = P_c + P_t$, where P_c is the power consumption of compression and P_t is the power consumption of transmission. If P_c increases, then P_t decreases. This implies that less bits can be transmitted because the transmission energy is proportional the number of bits to transmit. Therefore, image distortion increases. If P_c decreases, then P_t increases. The encoder will generate more bits to achieve the target distortion. This leads to an energy tradeoff between image encoding and wireless transmission. This energy tradeoff can conceptually described by the following minimization problem:

$$\min P = P_c + P_t = (P_{dct} + P_q + P_{entropy}) + P_t \tag{12}$$

In DCT based image compression, loss is introduced both in quantization process and DCT which, while in theory lossless, in practice introduces loss due to finite precision. And the two steps consume most of the compression power, almost 70%. Therefore, optimization of image compression energy consumption focuses on DCT and quantization [13].

Besides image coding, channel coding is needed to correct the bit errors that introduced to the video data stream. In this case, the overall bit rate is divided into two parts: image coding bit rate R_c and channel coding bit rate R_t. To minimize the overall image distortion, the parameters of the image encoder and the channel codes need to be adjusted for different input image sequences and different channel conditions. As the total bit rate is restricted by the limited wireless channel bandwidth, bit allocation between source and channel coding must be optimized. The encoder settings can be adjusted to achieve the allocated bit budget.

Image compression distortion and image transmission distortion are uncorrelated with each other, and they can be estimated separately. D_c is a function of image encoding energy consumption P_c and source coding bit rate R_c, which is denoted by $D_c(R_c, P_c)$. D_t is a function of the transmission energy consumption P_t and transmission distance d, which is denoted by $D_t(P_t, d)$. Therefore, the resource allocation and performance optimization of wireless video sensor can be formulated as follows:

$$\min_{\{P_c, P_t, R_c\}} D = D_c(R_c, P_c) + D_t(P_t, d) \qquad s.t. P_c + P_t \le P \tag{13}$$

As the total bit rate is restricted by the limited wireless channel bandwidth, bit allocation between source and channel coding must be optimized. The encoder settings can be adjusted to achieve the allocated bit budget.

Due to varying channel conditions and input images, the system parameters are required to be optimized jointly in time to maintain the total system energy minimum under the constraints of the expected image distortion and transmission rate. Using the energy consumption and distortion models of image compression and image transmission and the optimal configuration of the control parameters, the wireless video sensor is able to achieve the optimized power consumption and image distortion. The following steps should be performed to optimize the resource allocation:

(1) Collect scene activity statistics and classify the scene. Scene activity is coarsely divided into static and motion by motion detection.

(2) Encoder complexity control.

(3) Energy consumption and distortion models parameters update.

While there is no object motion in the monitoring scene, the input of the encoder is stationary. Only low frequency coefficients of DCT blocks will be processed to minimize the number of operations at each stage of the compression scheme. Pruning algorithm calculating k×k part of the DCT coefficients, (k=1,…,8), reduces the computation complexity and also decrease the image quality. And large quantization step size will be used. As the low frequency coefficients monopolize most of the signal energy, there will be a little information loss. While there is object moving or intruding in the monitoring scene, the monitoring image sequences are of great interest to the user. To achieve the distortion requirement, all the DCT coefficients will be processed, and small quantization step size will be used.

The required number of multiplications (M) and the total number of additions (A) for the N×N DCT is given by following equations, N is a power of two.

$$M = (N^2 / 2)\log_2 N \tag{7}$$

$$A = (5N^2 / 2)\log_2 N - 2N + 2 \tag{8}$$

Pruning algorithm calculating lower DCT coefficients, N0 is a power of two, the number of multiplications (M_{N_0}) and additions (A_{N_0}) for the computation of N0×N0 points are

$$M_{N_0} = (3/4)N^2 \log_2 N_0 \tag{9}$$

$$A_{N_0} = (2N^2 + N_0^2)\log_2 N_0 + N^2 - 3N_0^2 + 2N_0 \tag{10}$$

The quantization table is central to the compression/fidelity performance of JPEG coding. For the image compression it is necessary to develop a new quantization table to achieve a better energy saving than the JPEG standard quantization table.

V. SIMULATION RESULTS

To analyze the relationship between encoding complexity, image distortion and image data rate, several simulations are conducted using Matlab. Figure 2 shows how the PSNR evolves with k for the three images. It is obviously that the energy consumption for image compression is increasing as the k increases, therefore the PSNR increases. The test image sequences ‘Lena’, ‘Window’ and ‘Beach’ are in different resolutions. ‘Lena’ represents the images that contain much information, which can be classified as a high frequency images with high spatial details. ‘Window’ represents the images that contain little information and can be classified as a high frequency image with low spatial content. ‘Beach’ represents images that containing less information and can be classified as low frequency image with low spatial details. Pruning algorithm calculating k×k part of the DCT coefficients, (k=1,…,8), reduces the computation complexity and also decrease the image quality. Figure 2 show how the PSNR evolves with k for the three images. It is obviously that the number of multiplications, additions and memory accesses for DCT is increasing as the k increases, therefore the energy consumption for image compression increases.

The fidelity loss in JPEG coding occurs entirely in quantization, and much of the compression is gained by run length coding of coefficients with quantize to zero. Therefore the quantization table is central to the compression/fidelity performance of JPEG coding. For the image compression it is necessary to develop a new quantization table to achieve a better energy saving than the JPEG standard quantization table.

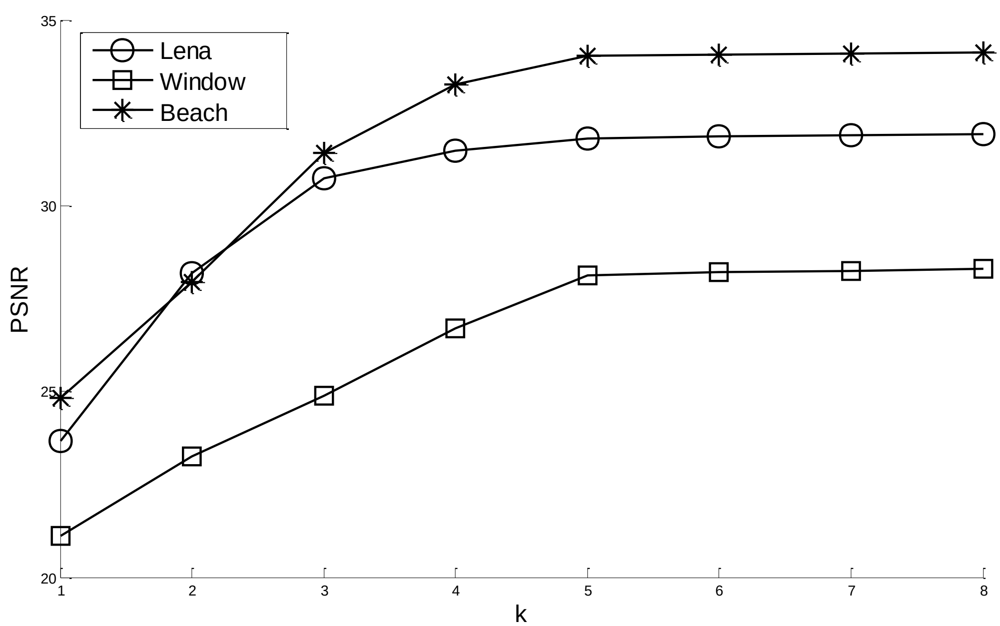

Figure 2. PSNR variations with k for three images

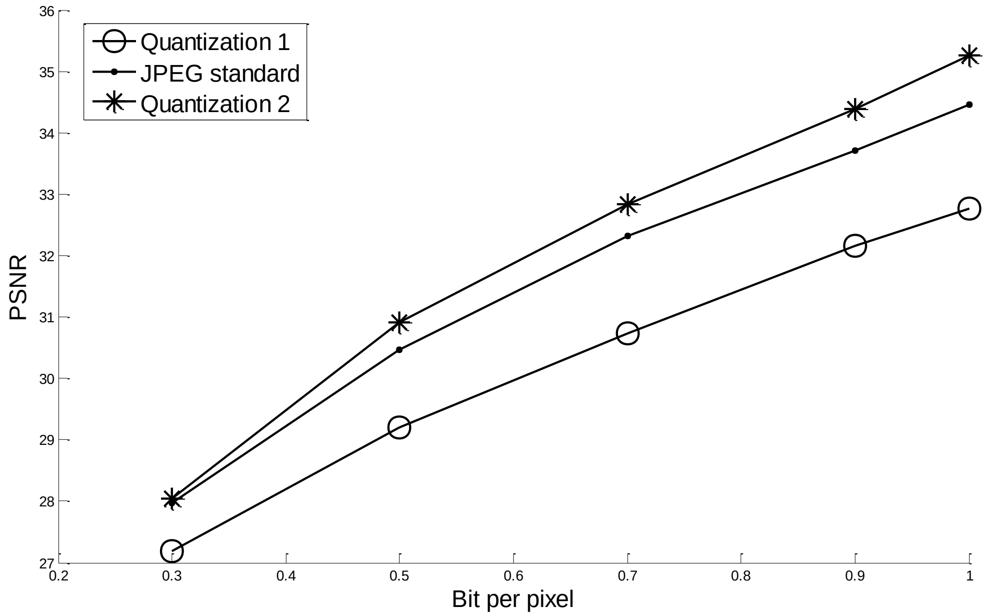

Figure 3. PSNR comparisons of three quantization tables on Lena image

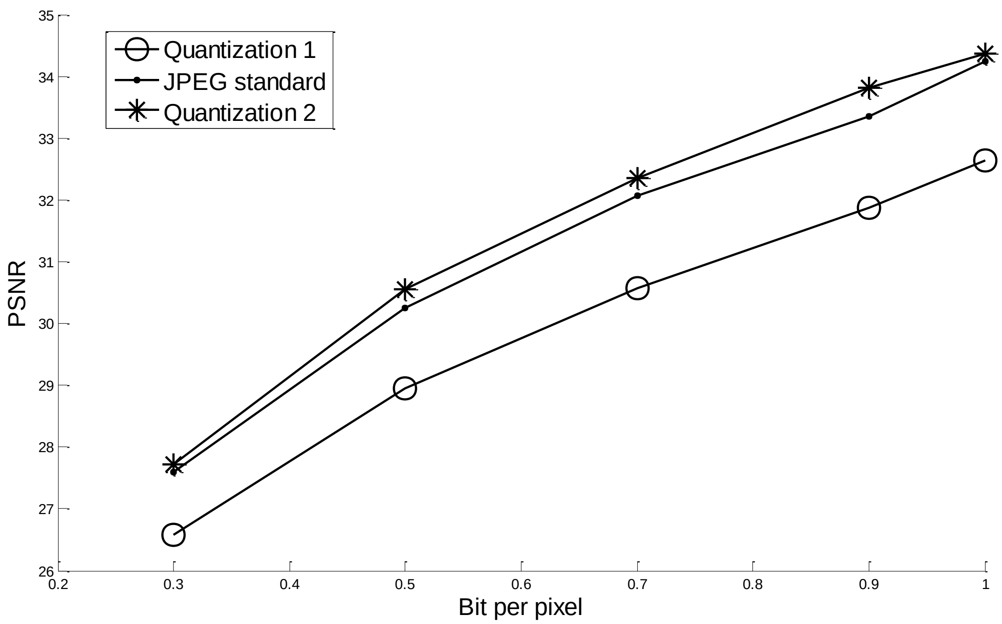

Figure 4. PSNR comparisons of three quantization tables on Peppers image

JPEG's quantization step sizes largely determine the rate-distortion tradeoff in a JPEG compressed image. Using the JPEG standard quantization tables is suboptimal since they are image-independent. Therefore, it is optimal to adapt the quantization table according to the scene activity in WMSN. Comparative performance is studied in terms of PSNR considering three quantization tables. Quantization table used in JPEG algorithm is applied to quantize the coefficients denoted as JPEG standard. Quantization table used in static scene image frame denoted as Quantization 1. Quantization table used in motion scene image frame denoted as Quantization 2. Quantization simulation results for image ‘Lena’ and ‘Peppers’ are shown in Figure 3 and Figure 4.

We test the proposed image compression scheme on PETS’2000 (IEEE International Workshop on Performance Evaluation of Tracking and Surveillance 2000) test datasets, which are the outdoor parking lot surveillance images of people and vehicle tracking. Test image sequence is consisted of 1452 frames at 25 Hz (58.08 seconds), single camera. The original image is 768×576 JPEG format color image，which is switched into the commonly used surveillance image format SIF (source input format) that is 320×240 gray scale image.

Table1 shows how the compression ratio affects the image quality of JPEG compression and frame rate for different values of the quality of JPEG compression. It is obviously that if compression ratio increases, the image quality increases, but frame rate decreases.

Table 1 Image quality and Maximum number of images per second that can be transmitted for different compression ratio

Compression rate	**Image quality**	**Frame rate**
Q0	1.29%	22.17
Q1	1.94%	14.71
Q2	2.80%	10.17
Q3	3.61%	7.89
Q4	4.30%	6.62
Q5	5.01%	5.69
Q6	5.78%	4.94
Q7	7.01%	4.07
Q8	9.08%	3.14

Q9	14.10%	2.02
Q10	45.81%	0.62

VI. CONCLUSION

In this paper, based on the study of DCT based coded image communication performance on video sensors in WMSN, energy consumption and image distortion models for image compression and transmission under energy constraints are derived. Then an energy-minimized resource allocation scheme is presented, which adapt encoder complexity according to the video scene activity. Simulation results indicate that our proposed scheme can save sensor energy significantly except for small quality degeneration of reconstructed images and a little more occupied transmission rates.

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