Battery-Aware Wireless Video Delivery

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Abstract. Feasibility and popularity of mobile multimedia have made video communications between mobile devices a rising trend with a wide range of applications. However, two main problems have emerged. First: in most of mobile devices, the power-hungry multimedia processor relies on the battery as the only form of power resource and the characteristics of a battery keep changing as the discharging operation goes. How to wisely utilize the energy stored in batteries on mobile device becomes a critical issue in designing a wireless video communication system. Second: in order to achieve QoS on mobile devices, the requested video chip has to be displayed under a given standard of quality. Therefore, it is also necessary for the received video to satisfy the constraint of an acceptable level of distortion. To analyze and optimize the communication quality and energy consumption behavior of battery-driven wireless video communication systems, we propose an optimization framework which takes into account the characteristics of battery driven devices by considering the relation between energy consumption and capacity discharging behavior of battery. In our framework, the video coding and transmission parameters are jointly optimized to minimize the battery capacity consumption under a predefined level of expected received video distortion. Experimental results indicate the efficiency and effectiveness of the proposed optimization framework.

Keywords: multimedia, video, battery, wireless communication system, QoS, distortion.

1 Introduction

Technologies in video compression and transmission over wireless communication networks have enabled mobile multimedia on portable wireless devices, such as cellular phones, laptop computers connected to WLANs, and cameras in surveillance and environmental tracking systems. Video coding and streaming are also envisioned in an increasing number of applications in the areas of battlefield intelligence, reconnaissance, and telemedicine. Present 3G and emerging 4G wireless systems, and IEEE 802.11 WLAN standards have dramatically increased the transmission bandwidth, and therefore, resulted in a great amount of personal communication users on video streaming applications. Although wireless video communications is highly desirable, a primary limitation in wireless systems is

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the basic design architecture that most mobile devices are typically powered by batteries with limited energy capacity. This limitation is of fundamental importance due to the high energy consumption rate in the duality of encoding and transmitting video bit streams during multimedia communications. From the perspective of battery-aware design and power management, how to wisely decide the energy allocation is a critical issue in order to efficiently use battery energy to guarantee a required lifetime and avoid task failure or malfunction due to the exhaustion of battery capacity before the whole video delivery task is finished.

The lifetime, or time-to-failure, of one battery is the time when it becomes fully discharged. Once the battery is exhausted, the mobile system shuts down. According to different acceptable distortion levels on wireless video communication and characteristics of one specific type of battery, we need to jointly consider a series of configurations in related modules and operating procedures during source coding and transmission to minimize the battery capacity under a certain constraint on distortion.

So far, there has been no dedicated analytical framework investigating an entire wireless video communication system where mobile devices use regular battery as the only form of power source in literature. And no experimental analysis on battery performance or optimization under a specific wireless multimedia platform has been performed. An analytical framework was presented to address the Power-Rate-Distortion relationship of a generic video encoder in [1]. However, video transmission was not considered in the evaluation of distortion and power consumption. Although some work [2,3,4] analyzed the energy efficiency of both video coding and transmission, the issue of power consumption was addressed without specifying the underlying characteristics of battery driven devices and no solution to minimize capacity consumption under the constraint of video quality is presented.

In this paper, we develop an optimization framework for wireless video delivery under the constraint of the video distortion required in a wireless video communication system. We first discuss the experimental methods and models to analyze the energy consumption in video encoding and transmission. Based on the analytical results, the problem of battery-aware wireless video coding and delivery is formulated to jointly select the video coding and transmission parameters to minimize the battery capacity consumption under the constraint of expected end-to-end received video distortion imposed by the desired video quality requirement. Our framework aims at the joint optimization of video coding and wireless transmission from the perspective of battery capacity condition.

This paper is organized as follows. Section 2 presents the formulation of the problem to solve. In section 3, measurements of energy consumption for video encoder and models for video stream transmission are introduced. Section 4 presents the method to calculate the expected distortion of a wireless video communication system. Analysis of working status of battery driven equipment is discussed in Section 5. Optimization method and framework are proposed in

Section 6. Section 7 presents the experimental results. Some concluding remarks are given in Section 8.

2 Problem Statement

2.1 Energy Consumption on Video Coding

To analyze the power consumption on video coding in a portable device, first, we need to determine the computational complexity of video coding at the encoder. Here, the computational complexity is measured by the running time of processor when video coding processes are under operation. Then, based on the power management technology of the underlying microprocessor in the mobile device, such as DVS CMOS circuits design technology [5], we can measure the energy used in those processes.

As shown in Figure 1, the major modules in a typical video encoding system include motion estimation (ME) and compensation, DCT, quantization, entropy encoding of the quantized DCT coefficients, inverse quantization, inverse DCT, picture reconstruction, and interpolation. In the literature, plenty of research results have been reported to evaluate and reduce the computational complexity, and thereby the power consumption of these modules [1,6,7]. It has been shown that, for each module in Figure 1, one or more control parameters together with the specific characteristics of a video chip can be extracted or selected to control the computational complexity of the module. For example, according to [1], the ME module could use the number of sum of absolute difference (SAD) as the complexity control parameter, while the modules of DCT, quantization, inverse quantization, inverse DCT, picture reconstruction may use a same complexity control parameter – the number of macroblocks (MB) which has nonzero DCT coefficients after quantization in a video frame. Let $\Lambda = [\lambda_1, \lambda_2, \cdots, \lambda_I]$ be the set of control parameters to control the computational complexity of these modules.

Therefore, the overall encoder complexity (or processor workload) ξ is a function of video processing parameters Λ, denoted by $\xi(\Lambda)$. Hence, the energy consumption of the underlying microprocessor to compress and encode one video clip, denoted by E_e, is a function of processor workload x_i, therefore, is also a function of Λ, denoted by

$$E_e = \Phi(x_i) \cdot t = E_e(\Lambda) = E_e(\lambda_1, \lambda_2, \cdots, \lambda_I), \tag{1}$$

where $\Phi(\cdot)$ is the power consumption model of the microprocessor [8], which can be obtained by measurement. For example, the power consumption model of the Intel PXA255 XScale processor is well approximated by $\Phi(x_i) = \beta \times x_i^\gamma$, where $\gamma = 2.5$, and β is a constant [9].

2.2 Energy Consumption on Video Transmission

To analyze the energy consumption on video transmission, we need to consider both the transmission scheme and the power control technology adopted by

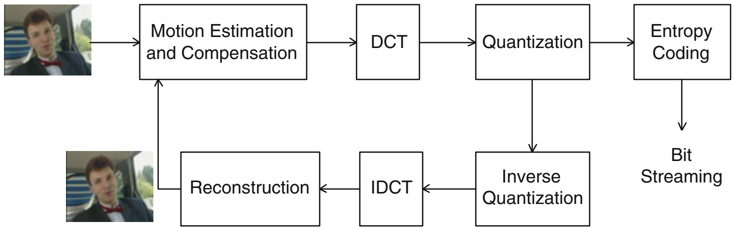

Fig. 1. Block diagram of a typical video encoder. For INTRA MB or frames, motion estimation and compensation are not needed.

the transmitter on mobile device. General energy E_t used in transmitting one video stream after video coding not only depends on wireless channel conditions, such as, instantaneous channel fading factor and channel noise power density, but also on transmission parameters, such as, frequency bandwidth, desirable packet error rate (PER), and modulation and coding schemes. Without loss of generality, let $\Theta = [\theta_1, \theta_2, \cdots, \theta_J]$ be the set of parameters affecting or controlling the transmission energy level. Therefore, the energy used in transmission can be represented by

$$E_t = E_t(\Theta) = E_t(\theta_1, \theta_2, \cdots, \theta_J). \tag{2}$$

2.3 Problem Formulation

Based on equations (1) and (2), the total energy consumption required from mobile device battery to deliver a video clip is

$$E_{tot} = E_e + E_t, \tag{3}$$

Because our framework aims at minimizing the capacity consumed from battery, it is necessary to convert energy into electric quantity. Once the hardware platform is set, we can derive the relation between the energy used for video delivery and the electric quantity consumed from the battery. The consumed battery capacity measured as the electric quantity can be express as

$$C_{tot} = f(E_{tot}), \tag{4}$$

Let D be the expected video distortion, and it depends on the video processing parameters Λ and the transmission parameters Θ. Different power supply results in different battery lifetime since the capacity of a given battery at certain status is fixed. Therefore, based on (3) and (4), the objective of the proposed framework is, for a specific video application, to determine the optimal values of the parameters $\{\Lambda, \Theta\}$ for a series of current video frames to minimize the battery capacity under the constraint on distortion D_{max} required by the specific application, which can be formulated as

$$\begin{aligned} &\min_{\{\Lambda,\ \Theta\}} C_{tot}(\Lambda, \Theta) \\ &\quad s.t. : D(\Lambda,\ \Theta) \leq D_{\max}. \end{aligned} \tag{5}$$

3 Energy Consumption Models and Measurement

3.1 Encoder Energy Consumption Model

Video coding or compression is a basic technology that enables the storage and transmission of a large amount of digital video data. Many standard video encoder systems, including MPEG-1/-2/-4, H.26x, and H.264/AVC employ a hybrid coding architecture based on DCT and Motion Estimation Compensation (ME/MC) scheme. Existing processes during wireless video communication include modules of ME (motion estimation), PROCODING (including DCT, inverse DCT, quantization, inverse quantization, and reconstruction) and ENC (entropy encoding). During video coding process, with the help of electric quantity measure equipment, the energy used in battery-powered multimedia processor can be derived from the operating time of CPU which enables the hardware resources to accomplish series of steps for video coding. On a specific video coding platform, the operating time of CPU depends on the characteristics of the specific video clip and complexity parameters selected in the steps of video coding. In the process of PROCODING, Quantization Parameter (QP), a parameter that controls the quality and bit rate of video compression, is a key factor to affect the number of nonzero MBs (NZMB) in one video frame which are needed to be coded. While the computation for quantization is independent of the bit rate, with a smaller quantization step size, more computation for variable length coding (VLC) is needed due to the increased number of nonzero coefficients. Many experiments have shown that all the steps together in PROCODING employ a large proportion of CPU occupancy and eat up more than 50% of the total energy consumption on encoder. Compared with other modules in source coding, PROCODING energy consumption is almost twice of the energy consumed in ME and six times of the energy consumed in ENC. Quantization step is the key complexity control parameter in the processes of PROCODING, therefore, it is reasonable for us to set quantization step q as the main optimal complexity control parameter in the video coding processes to calculate the energy used to encode a specific video clip on a certain hardware platform. The total time used in coding the whole video clip depends on the CPU running time spent on encoding every frame of this video. Denote the total number of frames in a video clip as n and the time used to encode kth frame as t_k. Then the total operating time of CPU T_e^{tot} to encode the a video clip can be expressed as

$$T_e^{tot} = \sum_{k=1}^{n} t_e^k, \tag{6}$$

On the other hand, total energy used in coding the whole video clip also depends on the energy E_e^k, which is used to encode the kth frame of this video. So the total operating energy of CPU E_e^{tot} used for coding can be written as

$$E_e^{tot} = \sum_{k=1}^{n} E_e^k, \tag{7}$$

It is possible for us to directly find the amount of electric quality used to encode every frame of a video by referring the corresponding experiment test result from equipment of energy measurement. In this way, once the hardware platform is decided, the energy in encoder for one frame is a function of the CPU running time t_k spent on coding this frame and the key complexity control parameter q_k chosen to compress the same frame. The function of total energy used in encoder can be given by

$$E_e^{tot} = \sum_{k=1}^{n} f_e(t_k, q_k). \tag{8}$$

where $f_e(\cdot)$ is the uniform way to calculate the energy consumption of one frame during coding processes.

3.2 Transmission Energy Consumption Model

The total transmission energy can be calculated by adding together the energy used on transmitting every frame of a video. This is given by

$$E_t^{tot} = \sum_{k=1}^{n} E_t^k, \tag{9}$$

where E_t^k is the energy consumption used for transmitting the kth frame. The energy used to transmit a frame depends on the compressed bits of this frame and channel transmission rate. Compressed bits of one frame is the size of a stream which is generated after coding processes of a video frame and mostly decided by the characteristics of the input video and the quantization step q applied on this frame. Channel transmission rate depends on the transmission bandwidth and adaptive modulation and coding (AMC) scheme. Different choice of AMC scheme applied in the transmitter will result in different transmission rates and spectral efficiency. Let W be the underlying channel bandwidth, and K_i be the transmission rate of AMC scheme i. Then, the resulting transmission rate when data is transmitted by using the ith AMC scheme is

$$R_i = K_i \cdot W, \tag{10}$$

If we use F_i to represent the compressed bits size of the ith frame after coding processes, then the energy used for kth frame can be denoted as

$$E_t^k = P \cdot \frac{F_i}{R_i} = P \cdot \frac{F_i}{K_i \cdot W}, \tag{11}$$

Where P is the transmission power. F_i can also be determined by referring the corresponding experiment test result. In general, the energy in transmission for one frame is a function of time spent on coding processes t_k, AMC scheme i and the complexity control parameter q_k chosen to compress the current frame.

Therefore the total energy consumption in transmitting a video clip can be written as

$$E_t^{tot} = \sum_{k=1}^{n} f_t(t_k, q_k, i). \tag{12}$$

where $f_t(\cdot)$ is the function to calculate the energy consumption used to transmit one frame.

4 Expected End-to-End Distortion

During the wireless video communication process, the total expected end-to-end distortion is caused during source coding and transmission. In order to acquire an accurate result of the distortion through the whole wireless video transmission system, in this work, we consider and calculate the overall end-to-end distortion instead of just simply adding the coding introduced-distortion and the transmission introduced-distortion together. Because a robust error concealment technique is necessary to avoid significant visible error in the reconstructed frames at the decoder, we consider a simple but efficient temporal concealment scheme used in our previous research [10]: a lost macroblock is concealed using the median motion vector candidate of its received neighboring mocroblocks (the topleft, top, and top-right) in the preceding row of macroblacks. The candidate motion vector of a macroblock is defined as the median motion vectior of all 4×4 blocks in the macroblock. If the preceding row of macroblocks is also lost, then the estimated motion vector is set to zero and the macroblock in the same spatial location is the previously reconstructed frame is used to conceal the current loss. Although some straight-forward error concealment strategies do not cause packet dependencies, as a generic framework, the more complicated scenario is considered here as a superset for the simpler cases. Due to the difficulty in computing the actual video quality perceived by the end users, in this work the received video quality is evaluated as the expected end-to-end distortion by using the ROPE method. The expected distortion is accurately calculated in real-time at the source node by taking all related parameters into account, such as source codec parameters (e.g., quantization, packetization, and error concealment) and network parameters (e.g., packet loss rate and throughput). Therefore, given the dependencies introduced by the above error concealment scheme, the expected distortion of slice/packet π_i can be calculated at the encoder as

$$E[D_i] = (1-p_i)E[D_i^R] + p_i(1-p_{i-1})E[D_i^{LR}] + p_iPi - 1E[D_i^{LL}], \tag{13}$$

where p_i is the loss probability of packet π_i, $E[D_i^R]$ is the expected distortion of packet π_i if received, and $E[D_i^{LR}]$ and $E[D_i^{LL}]$ are respectively the expected distortion of the lost packet π_i after concealment when packet π_{i-1} is received or lost. The expected distortion of the whole video frame which contents m packets, denoted by $E[D]$, can be written as

$$E[D] = \sum_{i=1}^{m} E[D_i], \tag{14}$$

Generally multiple modulation and coding schemes are available to wireless stations in a wireless data network to achieve a good tradeoff between the transmission rate and transmission reliability. Modulation schemes that allow a larger number of bits per symbol, have symbols closer to each other in the constellation diagram, which may result in more error in decoding. Varying code rates can be employed with each modulation scheme to adapt to changing channel conditions by allowing more redundancy bits for channel coding (lower code rate k/n) as channel conditions deteriorate. As the code rate decreases, the effective data rate is reduced, and hence the achievable throughput decreases. We set the term scheme i to refer to a specific choice of AMC scheme. The probability of error in a packet of L bytes, for a given AMC scheme i, as a function of the bit error probability $p_{b,i}$, can be express as $p_{e,i}(L) = 1 - (1 - p_{b,i})^{8L}$. Moreover, $p_{e,i}$ can also be approximated with sigmoid functions [11,12] in the form of

$$p_{e,i}(L) = \frac{1}{1 + e^{\lambda(x-\delta)}}, \tag{15}$$

where x is the Signal-to-Interference-Noise-Ratio (SINR). Table 1 shows the sigmoid parameters (λ, δ) for the 8 AMC schemes in modeling packet transmissions over an 802.11a WLAN network. From this table and (15), it is easy to see that $p_{e,i}$ depends on the specific AMC scheme i and so is the overall distortion since the end-to-end distortion is the function of $p_{e,i}$. Once the packet error probability is calculated, the expected end-to-end distortion can be derived based on equations (13) and (14).

We have noted that, except for the characteristics of the input video, the quantization parameters (QP) applied in source coding procedure play another critical role in contributing the total distortion since the larger the quantization step size is, the more small DCT coefficients will be lost. Thus, from (14), different levels of distortion will be achieved under different levels of QP. In other words, the value of quantization step q needs to be considered as another parameter to control the total distortion. Therefore, for a specific platform, the total expected distortion associated with AMC scheme i and QP q can be denoted as

$$E[D]_{tot} = D(q, i). \tag{16}$$

Table 1. Approximation of packet error probability for different AMC schemes

Mod Scheme	δ (dB)	λ (dB^{-1})	$CodeRate$ $(bits/symbol)$	$AMCScheme$ (i)
BPSK	2.3	0.640	0.5	1
BPSK	6.1	0.417	0.75	2
QPSK	5.3	0.461	1	3
QPSK	9.3	0.444	1.5	4
16-QAM	10.9	0.375	2	5
16-QAM	15.1	0.352	3	6
64-QAM	18.2	0.625	4	7
64-QAM	21.2	0.419	4.5	8

5 Battery Capacity Measurement

Mobile devices are mostly driven by battery. Once the battery becomes fully discharged, the battery-powered electronic system goes off-line. Available battery capacity has a nonlinear relationship with its discharging current due to the battery current effect. That means a battery tends to provide more energy at a lower discharge current. Some battery lifetime and capacity prediction models are available, like the analytical model in [13]. But considering that analysis and optimization of our research is mainly base on the profiles of distortion and energy consumption, precise data measurement is necessary to make the work more practical and applicable. So we choose to execute a series of real experiments to build the experimental profile, which includes all the real time data information of the parameters we need for optimization and analysis. Once such profile is set up, electronic parameters, like voltage, current and electric quantity used for every steps of the operation, can be derived from this profile. By describing the expression of (4), the capacity consumed from the battery can be calculated from the energy consumption. The total capacity needed from battery to achieve wireless video delivery can be derived from the follows

$$C_{tot} = C_e + C_c = C_e + \frac{E_t}{V}, \tag{17}$$

where C_e is the electric quantity consumed to execute the video coding, and this value can be derived from the profile result of experiment. C_c is the electric quantity consumed for video transmission, and this can be calculated from the transmission energy consumption model introduced in section 3 if the transmitter operating voltage V is known. Combine with (11) and (12), we get

$$\begin{aligned} C_{tot} &= C_e + \frac{\sum_{k=1}^{n} P \cdot \frac{F_i}{K_i \cdot W}}{V} \\ &= C_e + \frac{\sum_{k=1}^{n} f_t(t_k, q_k, i)}{V}. \end{aligned} \tag{18}$$

6 Optimized Battery Capacity Framework under Distortion Constraint

In order to solve the the formulated optimization problem in Section 2, two profiles need to be established in advance. The first profile is about how the pattern of the expected received frame distortion changes according to different set of choices on quantization parameters q and AMC scheme i. The second is how the battery capacity used for the delivery of one frame is decided by the same set of choice on QP and AMC scheme. Therefore, in our framework, we choose quantization parameters q and AMC scheme i to form a two dimensional independent vectorial variable. Let Q be the total options of QP, I the total optional AMC schemes. So every video frame has $Q \cdot I$ options of this vector. Because both parameters are the key control variables to determine the working pattern in both coding and transmission, we name this vector as the control vector, and denote it as (q, i) according to the definitions of previous sections.

Video is fundamentally different from other multimedia resources, for it basically comprises a group of separated video frames. When we deal with the optimization of battery capacity under the constraint of video distortion, it is not reasonable to figure out only one set of optimal control vector to process all the video frames uniformly, because the dynamics in video content and channel conditions make it necessary to adjust the QP and AMC parameters frame by frame. Therefore, we apply the optimization to figure out the best control vector toward each frame to minimize the battery capacity used to deliver each frame under the constraint of expected received frame distortion. From (16) and (18), we can see that the total expected distortion and total energy consumption are based on the choice of control vector used to code and transmit each video frames. For a specific video, after the execution of experiment and model applications, the expected received video distortion and battery capacity used for delivering the whole video clip can be calculated by referring to the received frame distortion and battery capacity used for delivering each frame.

7 Experimental Result

We conducted experiments to show the performance of the proposed framework. Four video sequences with varied contents (Carphone, Foreman, Coastguard, Mobile) in QCIF format are considered in our work. An Imote2 wireless sensor node which applies PXA271 XScale processor is used in the experiment. Arbin measurement system is in charge of monitoring and recording all the desired

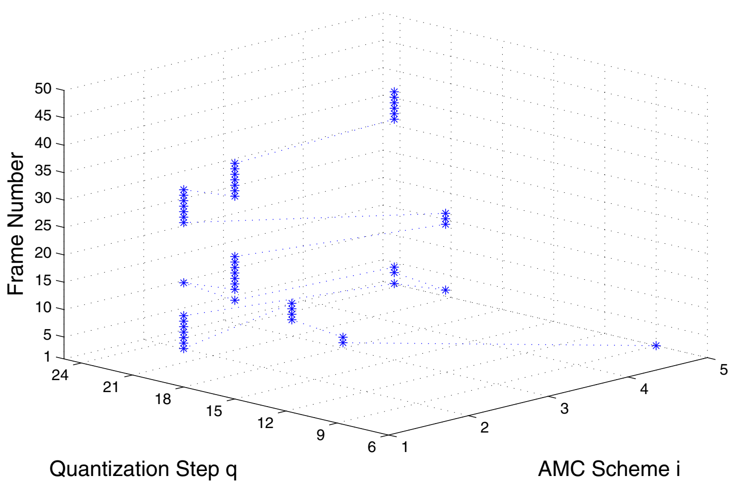

Fig. 2. The optimal solution achieving the minimized distortion without the battery capacity constraint

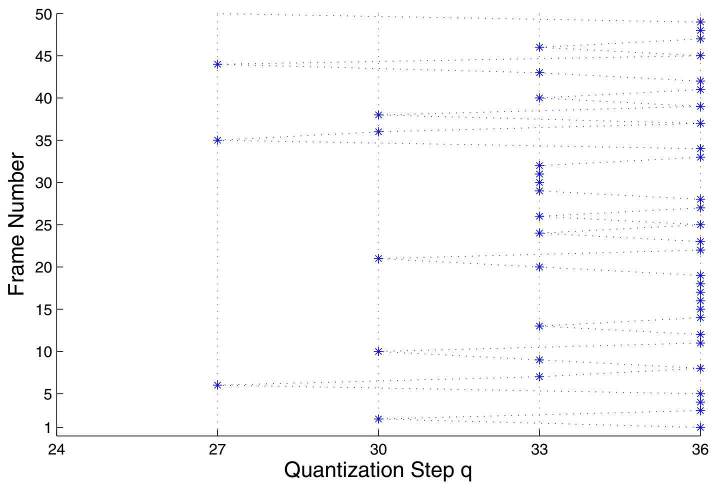

Fig. 3. The optimal solution achieving the minimized battery capacity consumption without the distortion constraint. (AMC Scheme i=8).

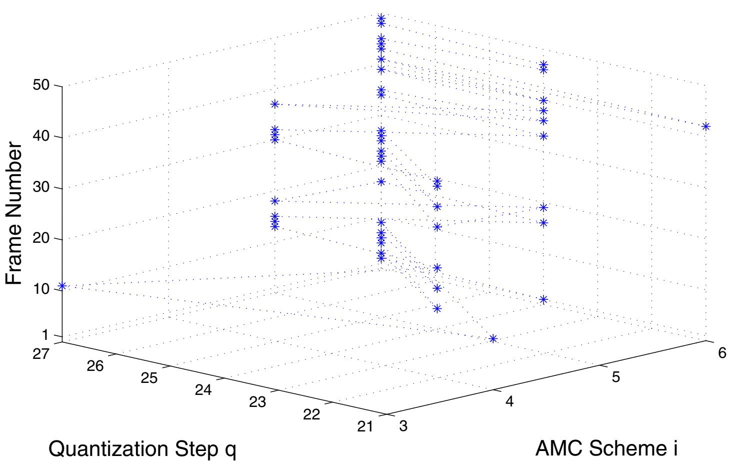

Fig. 4. The optimal solution under the constraint of 36 dB average frame distortion

electronic data. The Y-component of the first 50 frames of each video sequence is encoded with H.264 codec (JVT reference software, JM 16.2 [14]). We choose the quantization step size (QP) and AMC schemes listed in table 1 as the tunable source coding and transmission parameters. The permissible QP values are [9, 12, 15 . . ., 36]. According to table 1, the permissible AMC scheme i values are [1, 2,

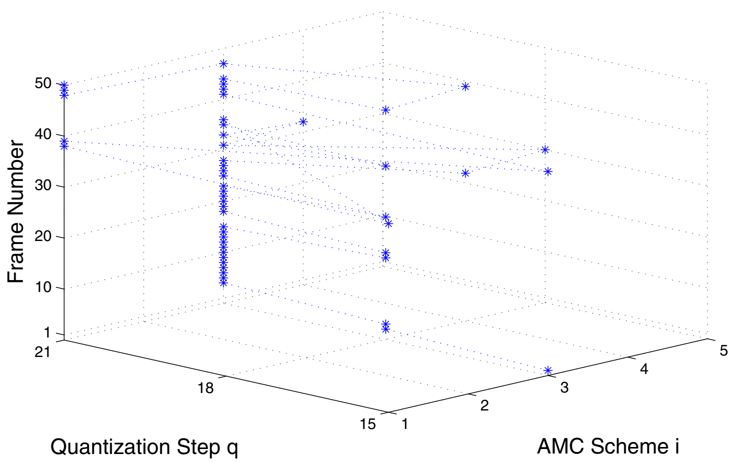

Fig. 5. The optimal solution under the constraint of 42 dB average frame distortion

3, . . ., 8]. Because different QP results in different bit rate. To maintain a smooth date rate and thereby a relatively constant power consumption on transmission to extend the battery lifetime, the difference of the selected QP for neighboring slices is limited within a threshold of 3. All frames except the first one are coded as inter frames. To reduce error propagation due to packet loss, 10 random I Macroblocks were inserted into each frame. The frames are packetized such that each packet/slice contains one row of MBs, which enables a good balance between error robustness and compression efficiency.

During an experiment by using the video clip Foreman, figure 2 shows the condition that no capacity constraint for video delivery was applied, and the optimization process chose the optimal solution which has the minimized distortion in each frame. In this case, the solution has a total PSNR of 2247.1 dB and average PSNR of 44.9 dB for each frame, battery capacity consumption is 0.0119 Ah. From the figure we can see that the control vector of each frame concentrates in the lower range of AMC scheme i and quantization step q. Figure 3 shows the scenario where no distortion constraint is applied for video delivery, and the optimization process chose the optimal solution which has the minimized battery capacity consumption in each frame. In this case, the solution has a total PSNR of 1462.4 dB and average PSNR of 29.2 dB for each frame, the battery capacity consumption is 0.0101 Ah. We can also see that the control vector of each frame concentrates in the higher range of the quantization step q, and all the frames are transmitted under the AMC scheme of number 8.

The optimization framework proposed in this paper was tested by three experiments under different values of distortion constraint. In the first experiment we applied the optimization toward the first 50 frames of the Foreman video clip, and set the average frame distortion constraint as 36 dB. After executing

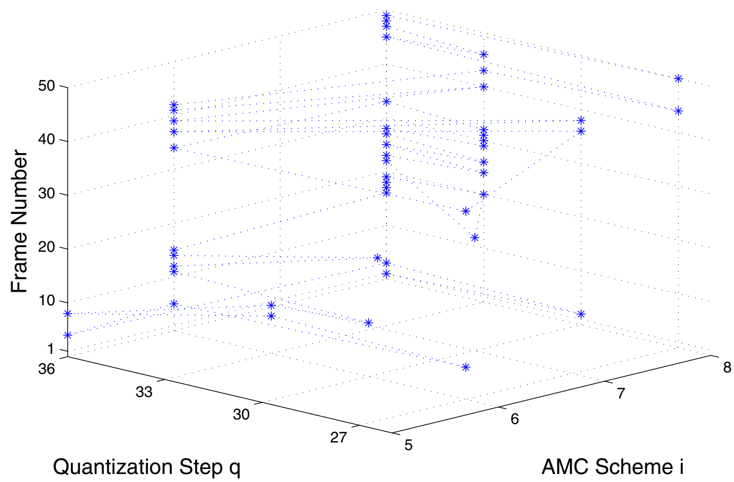

Fig. 6. The optimal solution under the constraint of 29 dB average frame distortion

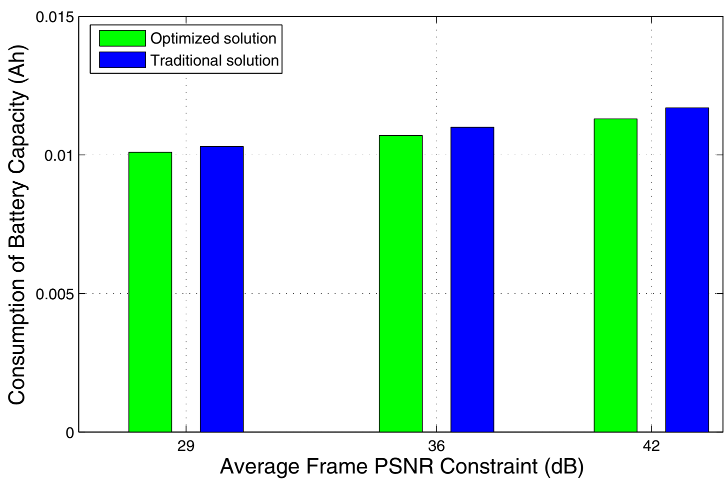

Fig. 7. Comparison of battery capacity consumption under three average frame distortion constraints

our framework, the control vector for each frame can be decided to minimize the battery capacity consumption and results in a received frame which has a distortion under 36 dB. Figure 4 shows the 50 control vectors corresponding to the first 50 frames of the tested video clip. Every point in the space represents an optimized control vector of one frame to satisfy the constraint. All the optimized

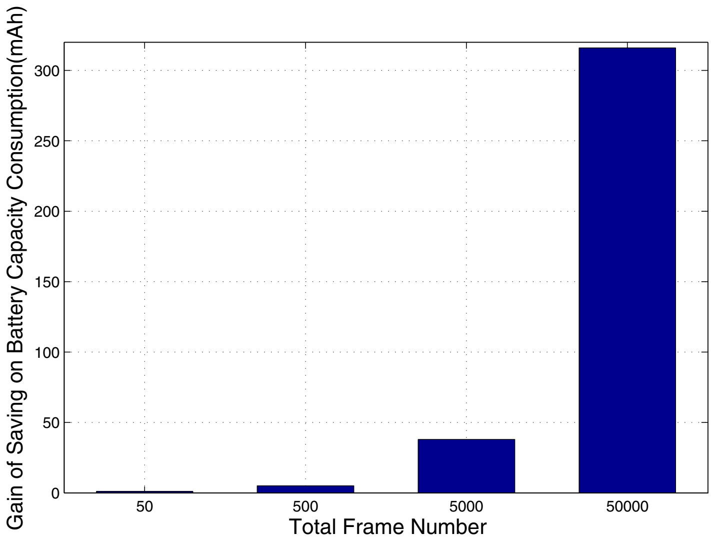

Fig. 8. Comparison of battery capacity saving in delivering 50, 500, 5000 and 50000 frames

control vectors of these 50 frames has formed an optimized solution for this video clip. By applying our optimization, this solution can still be figured out as the number of the video frames grows. Figure 5 and figure 6 show the other two testing results of establishing the optimized solutions under the average frame distortion constraints of 42 dB and 29 dB.

Figure 7 shows battery capacity consumption comparison between the optimal solution and traditional solution but satisfies the received framed distortion constraint. We can see that the solution selected by applying the framework has the most minimized battery capacity consumption under a certain video quality constraint. Figure 8 represents how much battery capacity can be saved according to the total number of video frames with proposed framework. In the figure, the gain of saving on battery capacity increases in an exponential fashion when the total number of video frames needs to be delivered increases. As a result, the proposed optimization can save considerable amount of battery capacity if it is applied to a relatively long video delivering case.

8 Conclusion

We developed an analytical framework for mobile wireless video communication systems driven by battery. A method to optimize the battery capacity consumption under a constraint of expected received video distortion is proposed. Based on analytical results, the video coding and transmission are jointly considered to minimize the battery capacity used for one video frame under the constraint of expected received frame distortion. Experimental results verified the efficiency and effectiveness of the proposed optimization framework.

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