Transmission Energy Minimization in Wireless Video Streaming Applications

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Abstract

Transmitter power is a valuable resource in wireless networks. Transmitter power management can have an impact on battery life for mobile users, link level QoS and network capacity. We consider efficient use of transmitter energy in a streaming application. We formulate an optimization problem that corresponds to minimizing the transmission energy required to achieve an acceptable level of distortion subject to a delay constraint. By considering jointly the selection of coding paramters and transmitter power we can formulate an optimal policy. We present results illustrating the advantages of jointly considering these two variables.

1 Introduction

Wireless networks are rapidly becoming an important component of the modern communications infrastructure. There is increasing demand by mobile users for services traditionally available only in wireline networks, such as video. Several important issues, such as transmitter power control, are unique to wireless networks and deserve special attention. In this paper, we consider the interaction of video compression and transmitter power adaptation. Our goal is to efficiently utilize transmitter energy while meeting delay and video quality constraints imposed by the video streaming application.

Video transmission over unreliable channels has been an active field of research. The negative effects of channel losses can be combated by using error resilience and concealment techniques [1] or by adapting the behavior of the encoder according to the conditions of the channel [2, 3, 4].

Transmitter power adaptation can be used to prolong battery life in mobile devices, maintain stable link QoS and reduce interference to other users. For these reasons, transmitter power control has received considerable attention [5, 6, 7] . In [6] , the problem of minimizing required transmission energy for streams with average delay constraints was studied. Critical backlog policies were found that minimize the total amount of energy expended at the transmitter subject to a constraint on the average delay. The tradeoff between delay and average transmission power was studied in [7] as a multiobjective optimization problem. The goal is simultaneously minimizing average transmission power and average delay.

Efficient transmission of video over a fixed rate wireless channel was considered in [8]. The objective was to spend the minimal amount of energy to transmit a video frame subject to an expected distortion constraint. This expected distortion was computed by taking into account the effect of the error concealment. In this paper, we incorporate the use of data rate adaptation into the optimization. Our goal is to minimize the amount of energy required to transmit a video sequence over a wireless channel while meeting the video quality and the delay constraints from the streaming application.

In the next section we present the problem formulation in detail. In Sec. 3, we present a solution based on lagrangian relaxation and dynamic programming. Results and Conclusions are presented in Sec. 4.

2 Problem Formulation

We consider a system where video is encoded using a block based motion compensated (MC) technique, such as MPEG-4, to produce a stream of video packets. The resulting video packets are transmitted through a wireless channel. Each video packet is made up of a sequence of macro-blocks (MBs) and can be processed independently. The size of the packets and their relationship to slices or group of blocks (GOBs) is not explored in this paper. Instead, we will initially consider a simple packetization scheme where each packet is made up of a single macro block (MB). We therefore use the terms MB and video packet interchangeably.

In Fig. 1 a block diagram of the system considered here is shown. Video frames are captured and fed to the encoder buffer. The video encoder reads each MB from the encoder buffer producing a video packet that is transmitted over a wireless channel. The transmitter (Tx) can dynamically allocate communication resources at the physical layer for each packet in order to meet the delay constraints of the application and ensure reliable transmission. Several techniques for data rate adaptation have been incorporated into existing wireless standards (see for example [9] , for a survey of the currently available techniques). At the receiver (Rx), the incoming video packets are received and stored in the decoder buffer. The decoder reads video packets from this buffer and must display the video sequence in real-time, that is each captured frame must be displayed within an acceptable delay interval. The length of this interval depends on the nature of the application.

2.1 Delay Constraints

We denote by M, the number of MBs in a video frame. We assume a constant encoding and decoding time for each MB, T_{MB}. Then we can translate the constant end-to-end delay constraint on the frame into a constant delay constraint on each MB. We denote this delay constraint by T_{max} (refer to Fig. 2. Then, the delay experienced by each MB must meet the following constraint

$$\delta(k) \leq T_{max} \tag{1}$$

where $\delta(k)$ represents the delay introduced by the encoder buffer and the transmitter. Our goal is to assign to each MB a choice of coding mode and quantization step size, at the source coding level, and a transmission rate at the physical layer in order to obtain good video quality. MB k is encoded with quantizer $q(k)$ resulting

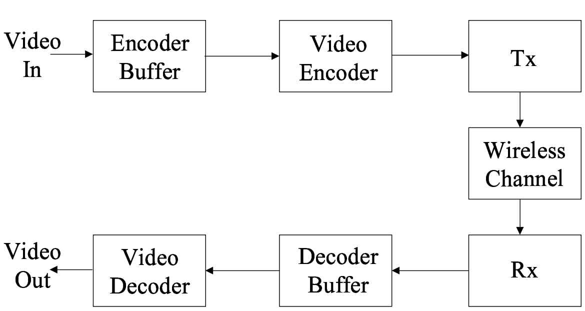

Figure 1: System block diagram.

in a video packet of size $B(k)$ bits and distortion $D(k)$. Transmitting this packet at rate $C(k)$ results in delay $\delta(k)$ given as,

$$\delta(k) = w(k) + \frac{B(k)}{C(k)}, \tag{2}$$

where $w(k)$ is the amount of time the packet must wait in the buffer before transmission; we refer to this as the waiting time. The second term in Eq. (2) is the transmission delay for MB k. This is the amount of time it takes to transmit $B(k)$ bits at a channel rate of $C(k)$ bits per second. The waiting time depends on the delay for the previous MB, $k-1$. Thus we can write,

$$w(k) = \delta(k-1) - T_{MB}. \tag{3}$$

2.2 Channel Model

We consider a slowly varying wireless channel with frequency nonselective fading. The fading is modeled as a finite state Markov chain with state space $\mathbb{H}$. The channel fading states transition periodically every T_c seconds. The channel fading transitions are governed by the transition probability matrix $\mathbf{A}$ of the Markov chain. At time slot l, we model the channel over which packets are being sent as a band-limited additive white Gaussian noise channel with gain $\sqrt{h(l)}$. We assume that the gain stays fixed during each time slot and is known at both the transmitter and receiver. If the desired transmission rate for the kth packet is $C(k)$, we assume that the required transmission power at each time slot is the minimum power such that the channel over which this packet is sent has Shannon capacity $C(k)$, i.e.,

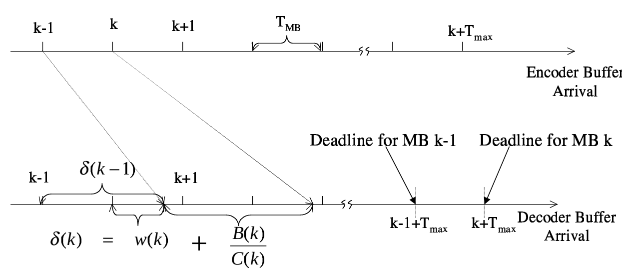

Figure 2: Components of Delay for each MB. Each MB must wait until the previous MB has been transmitted before it can be transmitted.

$$P(h(l), C(k)) = \frac{N_0 W}{h(l)} \left(2^{\frac{C(k)}{W}} - 1 \right). \qquad (4)$$

From Shannon's coding theorem, Eq. (4) gives a lower bound on the transmission power required to reliably transmit at rate $C(k)$; moreover for large enough packets, this bound will be approachable and will give a reasonable indication of the required power. The expected amount of energy required to transmit video packet k of size $B(k)$ bits at a rate of $C(k)$ bits per second can be expressed as

$$E(k) = \mathbb{E}_H \left\{ \sum_{l=0}^{L_k - 1} P(h(l), C(k)) T_c | h(0) \right\}, \qquad (5)$$

where L_k is the number of time slots required to transmit video packet k. This delay is given by

$$L_k = \left\lceil \frac{B(k)}{C(k) T_c} \right\rceil \qquad (6)$$

The expected energy required to transmit a packet depends only on the statistics of the channel and the size of the transmission delay L_k. This expected cost can be computed off-line and implemented as a table look up at the transmitter.

Formally, we want to solve the optimization problem given below:

$$\begin{aligned} \min_{q(k), C(k)} \; & \mathbb{E}_H \left\{ \sum_{k=0}^{M-1} E(k) \right\} \\ \text{s.t.: } & \mathbb{E}_H \left\{ \sum_{k=0}^{M-1} D(k) \right\} \leq D_T \\ & \delta(k) \leq T_{max}, \forall k, \end{aligned} \qquad (7)$$

where $\delta(k)$ and $E(k)$ are given by Eqs. (2) and (5) respectively. The initial conditions $w(0)$ and $h(0)$ are the initial wait time and the initial channel state, respectively.

3 Algorithm

In this section we present an algorithm to solve the optimization problem in Eq. (7). First, we relax the distortion constraint. Thus, we introduce a Lagrange multiplier $\lambda > 0$ and solve the following relaxed problem:

$$\begin{aligned} \min_{q(k), C(k)} \; & \mathbb{E}_H \left\{ \sum_{k=0}^{M-1} [E(k) + \lambda D(k)] \right\} \\ & \text{s.t.: } \delta(k) \leq T_{max} \end{aligned} \qquad (8)$$

This relaxed problem can be solved using techniques from Dynamic Programming (DP) [10]. By appropriately choosing λ, the problem of Eq. (7) can be solved within a convex-hull approximation by solving Eq. (8) [11]. Furthermore, the search for an appropriate choice of λ can be carried out by some fast convex search technique such as the bisection method.

3.1 DP Solution of Relaxed Problem

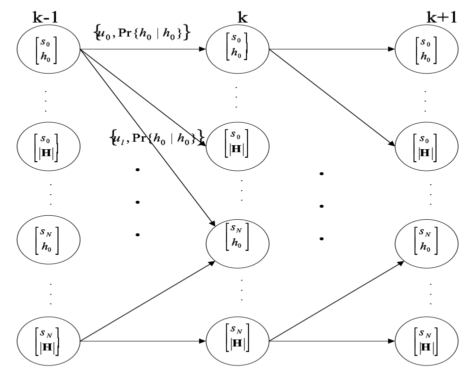

Figure 3: Trellis diagram.

In this section we describe in detail our solution to the relaxed problem of Eq. (8). First, we define the system state as

$$\mathbf{x}(k) = \begin{bmatrix} w(k) \\ h(k) \end{bmatrix}, \qquad (9)$$

where $w(k)$ is given in Eq. (3) and $h(k)$ is the channel state at time k. Note that $w(k)$ is real-valued and thus the resulting state space is infinite. We may approximate the solution to the problem by quantizing $w(k)$ and then applying DP to obtain the optimal solution to the resulting approximate optimization problem [10]. Let $\mathbb{S}$ be a finite subset of the nonnegative real numbers given by

$$\mathbb{S} = \{s_0, \ldots, s_N\}, \qquad (10)$$

with $s_l = (l \times T_{max})/N$. Then we have

$$w(k+1) = \left\lceil w(k) + \frac{B(k)}{C(k)} - T_{MB} \right\rceil_{\mathbb{S}}, \qquad (11)$$

where

$$\lceil w(k) \rceil_{\mathbb{S}} = \min\{s \in \mathbb{S} \mid s \geq w(k)\}. \qquad (12)$$

Finer quantization of $w(k)$ leads to better approximations to the optimal solution, at the cost of more computation.

Solving the resulting problem is equivalent to finding a stochastic shortest path through a trellis like the one shown in Fig. 3. In this diagram, three stages corresponding to MBs $k-1$ to $k+1$ are shown. At each stage, the possible system states are represented by a waiting time and a channel state. We have quantized the range of allowable $w(k)$ into a set of $N+1$ values, $\{s_0, \ldots, s_N\}$. For each of these we have $|\mathbb{H}|$ possible channel states. Thus the number of states for each stage is $(N+1) \times |\mathbb{H}|$.

Let $\mathbb{U}(\mathbf{x}(k))$ be the set of feasible choices of quantizers and channel rates when the system is in state $\mathbf{x}(k)$. The set $U(\mathbf{x}(k))$ is given as,

$$\mathbb{U}(\mathbf{x}(k)) = \left\{ (q(k), C(k)) \in \mathbb{Q} \times \mathbb{C} : \frac{B(k)}{C(k)} + w(k) \leq T_{max} \right\}. \tag{13}$$

For each choice of $u(k) \in \mathbb{U}(\mathbf{x}(k))$, the cost incurred by MB k is given by,

$$g(\mathbf{x}(k), u(k)) = E(k) + \lambda D(k). \tag{14}$$

In Fig. 3, each choice of $u(k)$ is represented by $|\mathbb{H}|$ branches, one for each possible channel state. Which branch is taken depends on the probability transistion matrix, $\mathbf{A}$ of the Markov chain describing the fading process of the channel.

We want to find a sequence $\{u(k)\}_{k=0}^{M-1}$ that minimizes the total expected cost in Eq. (8). We solve this problem by using DP. We start the algorithm at $k = M-1$, that is,

$$J^*_{M-1}(\mathbf{x}(M-1)) = \min_{\mathbb{U}(\mathbf{x}(M-1))} \{E(M-1) + \lambda D(M-1)\} \tag{15}$$

is calculated. Then for $k = M-2, \ldots, 0$, we recursively define

$$J^*_k(\mathbf{x}(k)) = \min_{\mathbb{U}(\mathbf{x}(k))} \mathbb{E}_H \left\{ g(\mathbf{x}(k, u(k)) + J^*_{k+1}(\mathbf{x}(k+1)) \right\}. \tag{16}$$

In carrying out (16) all combinations of $q(k)$ and $C(k)$ belonging to $\mathbb{U}(\mathbf{x}(k))$ are considered. This optimization clearly eliminates all choices $u(k)$ but one emanating from each state of the trellis. Given the initial state $\mathbf{x}(0)$, the optimal solution is obtained by backtracking. Clearly, $J^*_0(\mathbf{x}(0))$ is the optimal total expected cost of Eq. (8).

4 Experiments

In this section we present some experimental results that help to illustrate the tradeoffs studied in this paper. We consider the transmission of the first frame of the foreman sequence in QCIF format with maximum delay $T_{max} = 150ms$. In these experiments we set $N = 200$ in Eq.(10). The video packets are produced by an MPEG-4 encoder. We consider a set of eight available quantization step sizes given by $\mathbb{Q} = \{2, 4, 8, 16, 20, 24, 28, 31\}$. We consider transmission over a channel with bandwith $W = 500kHz$ and additive white gaussian noise with variance $N_0 W = 0.39$. The fading is modeled by a two state Markov chain with state space $\mathbb{H} = \{0.9, 0.1\}$. We use a symmetric transition probability matrix of the form

$$\mathbf{A} = \begin{bmatrix} p & 1-p \\ 1-p & p \end{bmatrix}, \tag{17}$$

with $p = 0.7$.

Sweeping λ in Eq. (8), results the convex-hull of Energy-Distortion points. These results are shown in Fig. 4. In this figure, we compare the convex-hull of operational Energy-Distortion points that can be obtained using our joint optimization with curves obtained using a two step procedure. In this two step procedure, we select the source coding parameters that use the minimum number of bits required to meet the quality constraints. We then transmit the encoded video sequence at a constant rate. Results for 100,200 and 300 kb/s are shown in the figure. Note that the curves obtained from the joint optimization always lie below the curves obtained using the two step procedure. From the figure, we can see that as we decrease the level of allowable distortion, the two step curves approach the joint curve. This is because more bits are required for the higher quality constraints and thus we need to transmit at 300 kb/s more often. Thus, the curve obtained using the two step procedure becomes a better approximation to the optimal.

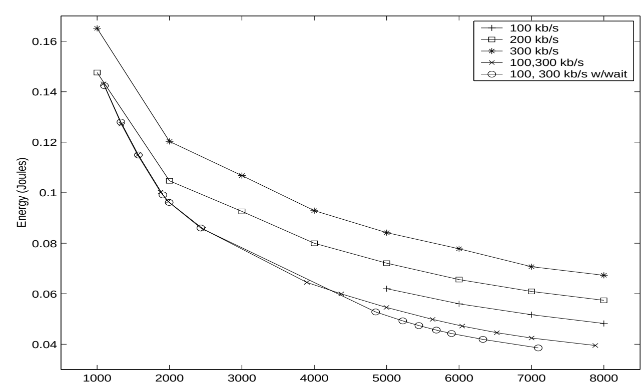

Figure 4: Convex hull of Energy-Distortion operational points.

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