Joint Source Channel Matching for Wireless Image Transmission [*]

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Abstract

Application of joint source-channel matching in heterogeneous multi-media environments will demand general source-channel optimization schemes suitable for a wide variety of source coding standards, channel coders, and variable channel conditions. We develop a general *approach for joint source-channel matching based on a parametric distortion model that can be accurately applied to most classes of source and channel coders. Our simulations indicate that it may be possible to obtain nearly all of the benefits of joint source-channel optimization by matching existing source and channel coding standards using the simple and general approach we propose.*

1 Introduction

Joint source-channel matching can provide significant performance gains in wireless communications systems carrying image and video traffic. Application of joint source-channel matching in heterogeneous, multimedia environments will demand general source-channel optimization schemes suitable for a wide variety of source coding standards, channel coders, and variable channel conditions. There has been significant work in the past on joint source channel coding for specific source and channel coders. We mention only a few here. In [1], Modestino examines the tradeoff between the rates of the source code and the channel code for a specific source and channel coder. In [2], Tanabe considers channel-optimized quantization in which source coding accuracy is traded for resistance against channel noise. More recently, Sherwood and Zeger [3] have examined unequal error protection for binary symmetric channels. Results in these papers indicate that exploiting the tradeoff between data and redundancy improves performance. However, these methods are typically based on a specific source coder, a specific channel coder, and a particular assumed channel. In practice, a variety of image and video transmission systems are in use and a general approach to source-channel matching is desirable.

We considered such a general approach based on parametric models for the source and channel coders in [4]. Here, we apply the general approach to a more flexible channel coder and a wireless channel model which includes fading. In the next section, the general optimization approach is described and in section 3, we apply the approach to two different image coders and various classes of channel coders. In section 4, the optimization algorithms are described, and in the final section the performance of our scheme is shown using simulations with real images.

2 A General Approach to Source-Channel Optimization

We propose a general matching scheme that can support heterogeneous standards and demands. The matching scheme can optimally match a wide range of source and channel coders. The key to our scheme is to perform an end-to-end optimization over both source and channel characteristics based on a parametric distortion-vs-bit error rate (BER) model for source coders. This lets us construct a more general source-channel matching optimization that can be applied to a variety of source and channel coders.

Many image and video source coding methods exist for removing redundancy in the source data and performing efficient encoding. These coders are optimized to give the best performance for a particular number of bits transmitted assuming that all the bits are received correctly. However, transmission over wireless channels introduces errors. In order to characterize the effect of channel errors on source coded data, we introduce bit errors to the source model. Let $D(b, R_s)$ be the distortion for the bth bit of R_s encoded bits. Either measured data, parametric models, or models fit to measured data from actual sources can be used to obtain this relationship.

Progressive coders which produce scalable bitstreams

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ordered in decreasing importance fit the proposed model well. Their extended rate-distortion surfaces are monotonic and smooth. Most source coders have some progressive element of the stream due to the inherent nature of compression. For non-progressive coders, the extended rate-distortion surface may not be monotonic and can have infinite peaks. In this situation, we can take advantage of joint source-channel matching by matching the source coding rate R_s to the channel coder and channel characteristics in source-rate-based optimization, as described later in this section.

Many channel coders exist for adding redundancy to a digital data stream and modulating it for transmission over a noisy channel. Channel coders are characterized by well-known generic measures of quality including BER, energy, and data rate. We use a channel description that is easily combined with the source model. The channel is modeled by BER as a function of symbol energy and code rate (i.e., $BER(Energy, R_c)$).

By using BER as the common parameter between the source and the channel, the source and channel characteristics can be combined to obtain distortion as a function of $Energy$ and rate $r = \frac{R_s}{R_{tot}}$ where $R_{tot} = R_s + R_c$, simplifying the joint optimization to the choice of the optimal $Energy$ and r for each symbol to minimize distortion.

Our philosophy is to consider the source coder and channel coder as functional blocks which must be matched together optimally.

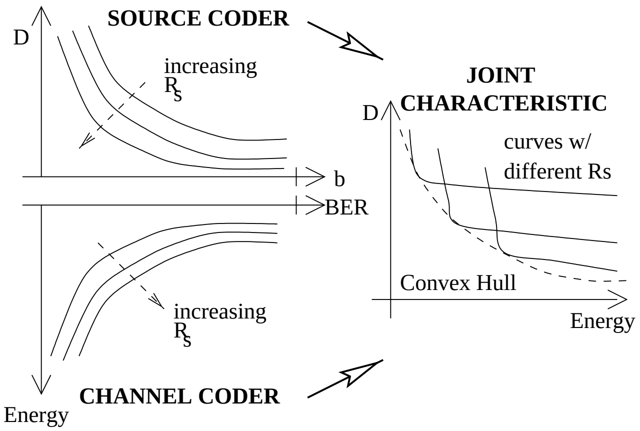

Figure 1: A graphical representation of source-channel matching where source and channel coder operating curves are combined to form the joint characteristic.

Figure 1 shows a simplified graphical representation of our approach. The channel coder is described as $Energy(R_s, BER)$ and the source coder is described by $D(b, R_s)$, where the channel coder uses R_s instead of R_c to match the source and channel descriptions. The joint curves are determined by choosing a particular BER and plotting all the $(Energy, D)$ points for each value of R_s. The convex hull of the joint characteristic represents the optimal energy distortion tradeoff. Each point on the convex hull of the $D(Energy)$ curve represents the optimal R_s, BER combination whereas existing methods consider only optimizing R_s for an arbitrary fixed BER.

Ideally, an optimal BER could be chosen for each bit. However, most channel coders do not have the flexibility to provide a different BER for each bit due to complexity constraints. So, we consider a block of source bits having the same BER. The expected distortion is then expressed as

$$E(D) = \sum_{i=0}^{N-1} D_b(i) P_b(i) + D(R_s) \prod_{i=0}^{N-1} (1 - P_b(i)), \quad (1)$$

where $D_b(i)$ is the distortion due to losing block i and $P_b(i)$ is the probability of losing block i.

The corresponding optimization problem is just the minimization of $E(D)$ subject to bandwidth and/or power constraints.

$$\min_{P_b, R_s} E(D) \text{ s.t. } P_{trans} \leq P_0 \text{ and/or } R_{tot} \leq R_0, \quad (2)$$

where $P_{trans} = \frac{E_{tot}}{T_{tot}}$ is the total transmission power per image, E_{tot} is the total energy per image, T_{tot} is the total time to transmit R_{tot} bits and P_0 and R_0 are fixed power and rate constraints. The solution determines R_s and the optimal P_b for each block. Lagrange multiplier and Feasible directions methods can be used to solve the constrained non-linear optimization problem.

The approach described here provides a distortion-based joint source-channel optimization. In some situations such as data transmission, non-progressive source coders and highly sensitive source coders which are intolerant of any bit errors, the $D(b, R_s)$ model can be simplified. The extended rate-distortion curve of the source is constant for all b because introduction of even a few errors corrupts the entire bitstream. Essentially all the source bits can be treated the same. The optimization problem can then be simplified considerably by performing a source-rate-based optimization of the channel coder. The channel coder is designed to provide the best protection for a particular source rate.

In this scenario, the number of source bits would be maximized to meet a particular failure probability $Pr(\text{fail})$ where the failure event is the occurrence of any bit errors. The optimization problem becomes

$$\max R_s \text{ s.t. } Pr(\text{fail}) \leq \delta, \quad (3)$$

where $Pr(\text{fail})$ is a function of R_s and $Energy$ per bit, and δ is the desired failure threshold.

3 Application to Specific Sources and Channels

We describe here some of the source and channel coders to which we have successfully applied our method.

3.1 Progressive Source Coder

For the first source coder we consider progressive image coders which produce a scalable bitstream. In particular, the Said and Pearlman [5] extension (SPIHT coder) of the embedded zerotree wavelet coding algorithm introduced originally by Shapiro [6] is a well-known progressive image coder with good performance on natural images. Due to the scalability of the progressive coded bitstream, the extended rate-distortion surface for this coder has smooth decay with increasing R_s. In addition, due to the embedded nature of the bitstream, the extended rate-distortion surface does not have to measured at different source rates. The extended rate-distortion curve can instead be found by measuring the distortion due to error in a particular bit of the source bitstream encoded at the *maximum* available source rate. To simplify analysis, distortion was measured in terms of the widely used metric of mean squared error (MSE). We have found that the extended rate-distortion curve is well approximated by a sum of four exponential terms. The distortion on the b^{th} bit is $D(b) = \sum_{k=1}^{4} c_k e^{-l_k b}$, where c_k and l_k are parameters specific to a particular class of images.

With the source model considered, the end-to-end distortion of the source-channel combination can be found according to (1). Due to the embedded nature of the SPIHT bitstream, this equation is modified slightly. E(D) depends on the location of the first bit error, since all bits after an erroneous bit are corrupted due to their dependency on the erroneous bit. The probability of block error is replaced with the probability of the *first* uncorrectable block error and the end-to-end distortion becomes

$$\begin{aligned} E(D) &= \sum_{i=0}^{N-1} D_b(i) P_b(i) \prod_{j=0}^{i-1} (1 - P_b(i)) \\ &\quad + D(R_s) \prod_{i=0}^{N-1} (1 - P_b(i)). \end{aligned} \tag{4}$$

With a particular choice of channel coder, an expression can be obtained for $P_b(i)$ in terms of the rate and energy in block i. The source-channel matching can then be performed over the parameters of the coders.

3.2 Non-progressive Source Coder

The Joint Photographic Experts Group (JPEG) coder is a widely used source coding standard for image transmission on the internet. Experimental results have shown that the JPEG-coded bitstream is highly sensitive to errors due to marker information in the bitstream. Even a single error can corrupt the entire JPEG reconstruction. For this coder, the simplified optimization problem of maximizing the number of source bits to meet a particular $Pr(\text{fail})$ constraint is suitable. The matching problem for the choice of a FEC channel coder is considered in [4].

3.3 Variable Energy Channel Coder

For the first channel coder we consider channel symbols with different energy which provide different levels of protection from the channel noise. In this example we choose unequal-energy, fixed-bandwidth Binary Phase Shift Keying (BPSK) symbols to be transmitted over an Additive White Gaussian Noise (AWGN) channel. By allowing a different energy, $E(i)$, for each block i, the BER is $p(i) = Q(\sqrt{\frac{E(i)}{L\sigma^2}})$, where $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{\frac{-x^2}{2}} dx$,σ^2 is the channel noise variance and L is the number of bits in a block.

3.4 Variable Rate Channel Coder

In many situations, designers must use off-the-shelf modems which have fixed symbol set and associated probability of error. In order to take advantage of source-channel matching, Forward Error Correction (FEC) techniques can be introduced to provide a variable symbol set and associated probability-of-error.

In this example, we use Reed-Solomon (RS) codes for BPSK symbols over an AWGN channel. A RS code defined by (n, k, t) is a length n code which contains $k = n - 2t$ information symbols, $2t$ symbols of redundancy and can correct t symbol errors [7]. When an (n, k, t) code has more than t symbol errors, the decoder will be unable to recover the original k data symbols and the entire code n can be considered as lost. With this analysis, the probability of incorrectly decoding a code is determined by the binomial probability density function (pdf)

$$P_b(t) = \sum_{v=t+1}^{n} \tbinom{n}{v} p_s^v (1 - p_s)^{n-v}, \tag{5}$$

where p_s is the symbol error probability. When any of the channel symbols making up the RS symbol are in error then the entire symbol is lost. So the symbol error probability becomes $p_s = 1 - (1 - p)^m$ using the binomial pdf, where p is the BER for BPSK.

One way that variable protection can be created is by blocking the available bandwidth into N RS codes of equal length L. Each code or block $i \in \{0, ..., N-1\}$ can contain a different number of protection symbols $T(i)$ according to the importance of its source symbols. Then, in the end-to-end distortion described in

(1), $P_b(i)$ is the probability of correctly decoding the block i, and $D_b(i)$ is the distortion due to losing block i. $P_b(i)$ is determined by the characteristics of the channel coder according to (5) and $D_b(i) = D(m \sum_{j=0}^{i-1} K(j))$, where $K(j) = L - 2T(j)$ is the number of source symbols in block j.

3.5 Adjustable Energy and Rate Channel Coder

In this channel coder we consider the flexibility to adjust both the rate and the energy in the channel symbols. We use a BPSK modulator which can adjust its energy per bit by allocating the total energy E_{tot} equally to a chosen total rate R_{tot}. This total rate is allocated between source symbols and protection symbols using a RS coder. The probability of block error for this channel coder is the same as in (5), where now $p = Q(\sqrt{\frac{E_{tot}}{\sigma^2 R_{tot}}})$ depends on the choice of R_{tot}.

This channel coder can offer substantial advantages over the variable energy or the variable rate channel coders. Variable rate techniques such as RS coders do not work well with high BER channel symbols. When the channel is relatively noisy, adjusting the symbol energy is essential to provide adequately low BER in the channel symbols. On the other hand, channels with relatively little noise require variable rate coders to provide error correction for infrequent errors.

3.6 Fading Channel

In wireless communications systems, fading is an important component of the channel response that arises due to multipath propagation of the signal. Unlike the memoryless channel models already considered, the fading channel has memory arising from overlap due to multipath characteristics. In order to characterize this channel, we consider interleaving the channel symbols. Interleaving is a common method for combating fading. When channel symbols are interleaved, the effect of the fade becomes dispersed over many symbol blocks and FEC can be used to correct errors within individual blocks. In addition, channel symbols can be assumed to be independently faded as Rayleigh random variables leading to a simple analytical result.

Consider using a BPSK channel coder overlaid with FEC over a fading. The BER, assuming interleaving, is derived in [7] as

$$p = \frac{1}{2}\left(1 - \sqrt{\frac{E_b}{2\sigma^2 + E_b}}\right), \tag{6}$$

where $E_b = E(i)/L$ is the energy per bit in block i with energy $E(i)$ and length L bits.

4 Optimization

With the models for the source coder and channel coder considered, optimization methods can be described for various source-channel combinations. Consider the combination of the SPIHT source coder and the variable energy channel coder. With the distortion expressed in terms of the transmission power, the overall system performance can be optimized by allocating the energy subject to a total energy constraint. The optimal set of energies $\mathbf{E}$ to minimize E(D) can be found by using gradient projection. At each step in the gradient projection algorithm, the set of energies $\mathbf{E}$ are adjusted opposite the gradient direction (which increases the total energy) and projected onto the fixed total energy E_{tot} surface.

Consider the combination of the SPIHT source coder and the variable-rate channel coder. With the distortion expressed in terms of the protection symbols, the overall system can be optimized by allocating the symbols subject to a total rate constraint. The optimal set of protection symbols $\mathbf{T}$ is found by using a gradient-based technique. At each iteration, the gradient determines the optimal number of protection symbols for a particular block $T(j)$ while holding all the other blocks fixed. Successive passes over the entire set of blocks account for the interdependency of the protection symbols.

When the SPIHT source coder is used with the adjustable energy and rate channel coder, the end-to-end distortion in (4) simplifies to

$$E(D) = \sum_{i=0}^{N-1} D_b(i)P_b(t)(1-P_b(t))^i + D(R_s)(1-P_b(t))^N. \tag{7}$$

When R_s is varied over $\{L, 2L..., NL\}$ where L is a fixed number of bits per block, we obtain an optimization problem over two parameters, the number of blocks to be transmitted and the number of protection symbols per block. Gradient-based search techniques can be used to solve the problem efficiently.

5 Results

In order to demonstrate the utility and flexibility of our approach, we have developed matching methods for the source coders and the channel coders described in section 3. Here we give the results for a few of these combinations.

We simulated the SPIHT-channel combinations for a 512x512, 8 bpp grayscale Lena image. Extended rate-distortion parameters for the SPIHT coder were determined for a compression rate of 1 bpp. All the simulation results are provided in terms of PSNR= 10log$(\frac{255^2}{MSE})$dB.

Figure 2 shows the performance of several different methods for various E_{tot} with $\sigma^2 = 0.5$. The lower curves are simulations of optimally matching the SPIHT source coder with the unequal-energy BPSK symbols channel coder (SPIHT-E). For comparison with this coder, we simulated a non-adaptive system with fixed energy per bit and associated rate R_s. Figure 2 shows that the adaptive system performance curve is the convex hull of the fixed energy systems.

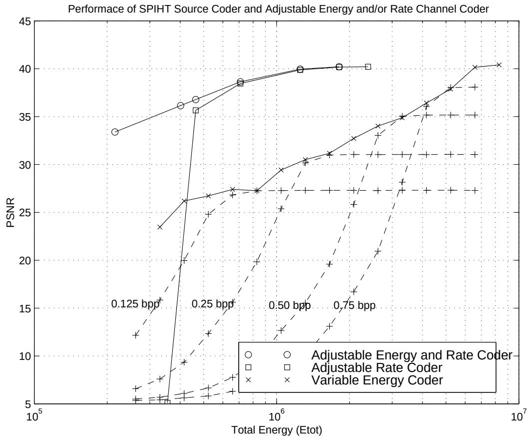

Figure 2: Simulation results for Lena using SPIHT source coder and various channel coders

Simulations of optimally matching the SPIHT source coder with RS channel coder (SPIHT-R) show that this system performs better than the variable energy system when E_{tot} is larger than $5 * 10^5$. According to the flexibility of the respective coders, the SPIHT-E coder performs better in high error channels where energy allocation is important while the SPIHT-R coder performs better in low error channels where infrequent errors can be corrected using FEC. Simulation results of the SPIHT coder with the adaptive energy and rate channel coder show that it has the best performance of the three channel coders, which is expected because each is a special case of this more flexible channel coder.

We can compare the results obtained here with results found in current literature such as [3] by converting E_{tot} to an equivalent average BER for a Binary Symmetric Channel. In low noise situations such as an average BER of 0.001, our results are 0.62dB better than results in [3]. In high noise situations such as an average BER of 0.1, our results are 0.86dB lower than results in [3]. These results suggest that it may be possible to achieve most of the benefits of fully joint source-channel optimizations using standard coders and the simple matching schemes proposed here.

We also applied our approach to the SPIHT source coder and adjustable energy and rate coder over a fading channel. Analytical simulation results in Figure 3 show that fading results in a significant loss of performance compared to AWGN channels. However, due to the severe effect of fading, the performance gains of an adaptive system over a fixed system are significant.

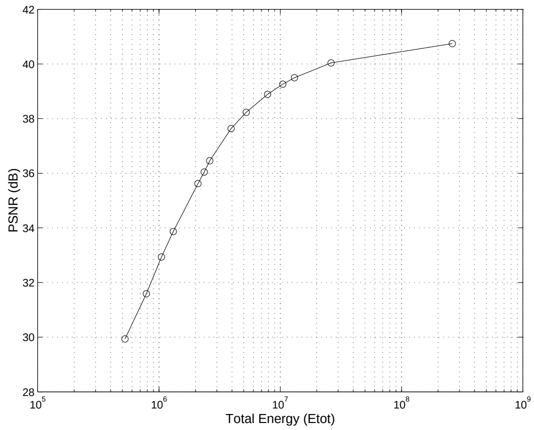

Figure 3: Analytical simulation results for Lena using SPIHT source coder and adjustable energy and rate channel coder over a fading channel

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