Joint Source Channel Matching for a wireless communications link *

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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.

I. Introduction

With the rapid growth of wireless communications systems, there is an increasing demand for wireless multimedia. Wireless image and video transmission, an essential component of wireless multimedia, poses a particularly important challenge that deserves attention for several reasons. Image and video transmission is the main system bottleneck because it requires far more bandwidth than other information sources such as speech or data.

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, 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. In a typical situation, system designers will choose prefabricated components for the source coder and the channel coder and must obtain the best performance within these constraints. 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 reality, a variety of image and video transmission systems are in use. A general approach to source-channel matching that can support various types of coders has yet to be considered.

In the next section, the general optimization approach is described for two different distortion criteria. In the Application to Specific Sources and Channels section, we apply the optimization to the specific case of image transmission using two different source coders and two classes of channel coders. In the Results section, the performance of our scheme is shown using simulations with real images.

II. 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-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 the concept of bit error probability (BEP) to the source model. The source coder is modeled by a sensitivity curve that determines the source distortion as a function of BEP for each bit and source rate (i.e., $D(BEP, R_s)$). Either measured data, parametric models or models fit to measured data from actual sources can be used to obtain these relationships.

Similarly, 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 bit error rate, power, and data rate. We use a channel description that is easily combined with the source model. The

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and code rate (i.e., $BEP(Power, R_c)$).

By using BEP 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 BEP 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 BEP and r to minimize distortion. Consider the graphical representation of our approach in Figures 1 and 2.

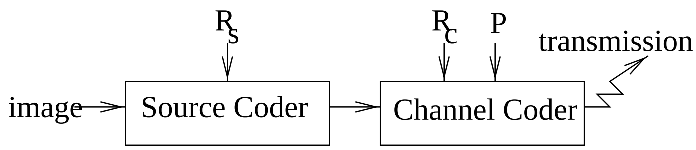

Figure 1: System Block Diagram where P is the power per bit and R_s and R_c are the source and channel rates respectively

Figure 1 shows the system block diagram of the source coder and channel coder with the parameters which can be adjusted to optimize performance. Our philosophy is to consider the source coder and channel coder as separate blocks which must be matched together optimally.

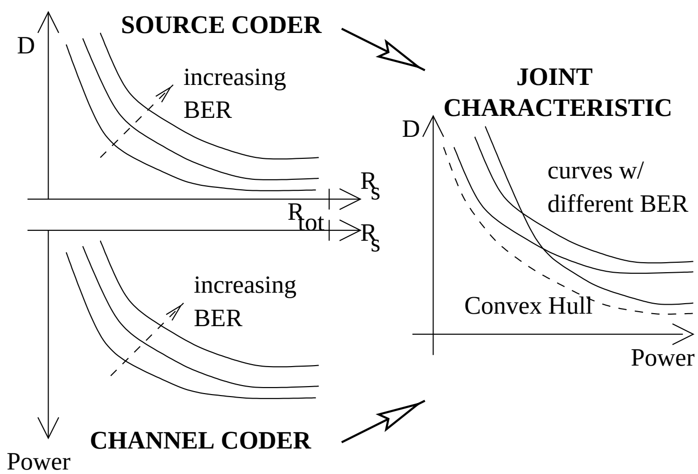

Figure 2: A graphical representation of source-channel matching where source and channel coder operating curves are combined to form the joint characteristic.

In Figure 2 we show a simplified graphical representation of our approach. The source coder is described by $D(BEP, R_s)$ and the channel coder is described as $Power(R_s, BEP)$, 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 BEP and plotting all the $(Power, D)$ points for each value of R_s. The convex hull of the joint characteristic represents the optimal power distortion tradeoff. Each point on the convex hull of the $D(Power)$ curve represents the optimal R_s, BEP combination whereas existing methods consider only optimizing R_s for an arbitrary fixed BEP.

Ideally, an optimal BEP could be chosen for each bit; source bits having the same BEP. The expected distortion is then expressed as

$$E(D) = \sum_{blocks} D(block) BEP(block) \qquad (1)$$

Gradient-projection-based methods can be used to solve the optimation problem

$$\min_{BEP,r} E(D) \text{ s.t. } P_{tot} \leq P_0 \text{ and } R_{tot} \leq R_0 \qquad (2)$$

where P_{tot} is the total available power and P_0 and R_0 are fixed power and rate constraints. The solution determines the optimal BEP and r for each block.

The approach described here provides a distortion-based joint source-channel optimization. In some situations such as data transmission and highly sensitive source coders which are intolerant of any bit errors, only low BEP can be considered in the $D(BEP, R_S)$ model. The source sensitivity curve is constant for all BEP because introduction of even a few errors corrupts the entire bitstream. The optimization problem can then be simplified considerably by performing a source-rate-based optimization of the channel coder. In this scenario, the number of source bits would be maximized to meet a particular failure probability P_{fail} where the failure event is the occurrence of any bit errors. The optimization problem becomes

$$\max_{R_s} \text{ s.t. } P_{\text{fail}} \leq \delta \qquad (3)$$

where P_{fail} is a function of R_s and power per bit, and δ is a small positive value. A Lagrange multiplier method can be used to solve this optimization problem.

III. Application to Specific Sources and Channels

To show the generality of our approach, we first apply it to a progressive source coder and two channel coders in a distortion-based optimization. Then, we also apply our approach to a highly sensitive source coder in a source-rate-based optimization.

A. Progressive Source Coder

For the first source coder we consider progressive image coders which produce a scalable bitstream. In particular, the Said and Pearlman [4] extension (SPIHT coder) of the embedded zerotree wavelet coding algorithm introduced originally by Shapiro [5] is a well-known progressive image coder with good performance on natural images. Due to the scalability of the progressive coded bitstream, the sensitivity curve for this coder has smooth decay with increasing R_s. The sensitivity curve for the coder was found by measuring the distortion due to error in a particular bit of the source bitstream encoded at the maximum available source of the widely used metric of mean squared error (MSE). We have found that the sensitivity 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, we can continue with our goal of finding the end-to-end distortion of the source-channel combination according to (1). This equation needs to be modified slightly for progressive coders. For a progressive coder, E(D) depends on the location of the first bit error, since all bits after the erroneous bit are corrupted due to their dependency on the erroneous bit. So, the BEP in (1) becomes the probability of the *first* uncorrectable bit error occurring in a particular block. In terms of the BEP for each bit, the expected value of the distortion becomes

$$E(D) = \sum_{b=1}^{NQ} D(b) p_b \prod_{j=1}^{b-1} (1 - p_j) \tag{4}$$

where p_k is the probability of error on the k^{th} bit, N is the number of source blocks, and Q is the number of bits per block. With considerable algebraic manipulation, we can obtain

$$E(D) = \sum_k c_k (\beta_{k,0} + \sum_{i=0}^{i=N-1} \beta_{k,i} \prod_{j=0}^{i-1} (1 - pe_j)^Q) \tag{5}$$

where, $pe_i, i \in \{0, .., N-1\}$ is the probability of a bit error in block$_i$, $\beta_{k,i} = pe_i e^{-l_k(iQ+1)} (\frac{1-\alpha_{k,i}^Q}{1-\alpha_{k,i}})$, and $\alpha_{k,i} = e^{-l_k}(1-pe_i)$.

B. Power Constrained Channel Coder

For the first channel coder we consider unequal-energy, fixed-bandwidth Binary Phase Shift Keying (BPSK) symbols over an Additive White Gaussian Noise Channel. By allowing a different power, P_i, for each block i, the probability of bit error is $pe_i = Q(\sqrt{\frac{P_i}{Q\sigma^2}})$, where σ^2 is the channel noise variance.

With the distortion expressed in terms of the transmission power, the overall system performance can be optimized by allocating the power subject to a total power constraint. The optimal set of powers $\mathbf{P}$ to minimize E(D) are found by using gradient projection. The gradient dD/dP_i is calculated using the chain rule as $\frac{dD}{dpe_i}\frac{dpe_i}{dP_i}$ where $dpe/dP_i = -\frac{e^{-P_i^2/(2Q\sigma^2)}}{2\sigma\sqrt{2\pi P_i Q}}$ and dD/dpe_i can be obtained by differentiating (5). At each step in the gradient projection algorithm, the set of powers $\mathbf{P}$ are adjusted opposite the gradient direction (which increases the total power) and projected onto the fixed total power P_{tot} surface.

A useful special case of this coder is the "on-off" coder in which a selected number of source bits are sent with equal power. We found that the simplified source-channel optimization for the on-off coder provides results that are within 0.5 dB of the coder considered above.

In many situations, modems available off-the-shelf are used as channel coders. These channel coders usually support only a fixed symbol set and associated probability of error, and FEC techniques must be used to achieve variable probability-of-error. In this example, we use Reed-Solomon (RS) codes for BPSK symbols over an AWGN channel. RS codes are a well-known class of block codes with good error correction properties. 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 [6]. There exist RS codes for various n, including $n = 2^m - 1$ where m is the symbol length in bits.

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 generally stops. Analysis of the number of errors in the decoded symbols when more than t symbol errors occur is difficult. To simplify the analysis, we consider the worst case that an entire code n is lost when more than t errors occur. With this analysis, the probability that a code is received correctly is determined by the binomial probability density function (pdf)

$$Pb(t) = \sum_{v=0}^{t} \binom{n}{v} ps^v (1 - ps)^{n-v} \tag{6}$$

where ps is the symbol error probability. The symbol error probability is a function of the number of channel symbols that form a RS symbol. Choosing byte-sized symbols for the RS code (i.e $m = 8$, $n = 255$), we can obtain $ps = 1-(1-p)^8$ using the binomial pdf, where p is the bit error probability for BPSK.

One way that variable protection can be created is by blocking the available bandwidth into N RS codes of equal length Q. 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, the expected value of the distortion can be written as

$$E(D) = \sum_{i=0}^{N-1} (1 - Pb_i) Db(i) \prod_{j=0}^{i-1} Pb_j \tag{7}$$

where Pb_i is the probability of correctly decoding the block i, and $Db(i)$ is the distortion due to losing block i. Pb_i is determined by the characteristics of the channel coder according to (6) and $Db(i) = D(m \sum_{j=0}^{i-1} K_j)$, where K_j is the number of source symbols in block j. The optimal set of protection symbols $\mathbf{T}$ is found by using a gradient based technique. The algorithm described next takes 3 or 4 iterations to converge.

Protection Symbols Allocation Algorithm

```
Iterate until convergence {
    For each i = 0, ...N − 1 do {
        Hold all T_k, k ≠ i fixed.
        Find the optimal T_i by moving
            in the ΔE(D)/ΔT_i direction.
    }
}
```

multiple iterations are used to successively refine $\mathbf{T}$. In each iteration, each of the T_i are refined by holding the other $T_k, k \neq i$ fixed.

We also consider a near-optimal simplification to the optimization problem in which each block has the same number of protection symbols. The motivation for this simplification is the channel coder characteristics described by Pb. We have found that the $Pb(T)$ function transitions rapidly as protection bits are added from $Pb = 0$ to $Pb = 1$. Due to this effect, equal protection for each block yields results almost as good as variable protection. When each block has the same number of protection symbols, T, the distortion simplifies to

$$E(D,T) = \sum_{i=0}^{N-1} Pb^i(1 - Pb)Db(i) \qquad (8)$$

where we explicitly specify T as a parameter in the distortion. Gradient techniques can be used to find T to minimize $E(D)$. Convergence of gradient-based algorithms is guaranteed since Pb and $D(b)$ are monotonically decreasing.

D. 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 synchronization information in the bitstream. Even a few errors can corrupt the entire JPEG reconstruction. For this coder, we consider a simplified optimization problem of maximizing the number of source bits to meet a particular P_{fail} constraint; that is, to assure that the image is successfully received without error with a probability $\geq 1 - P_{\text{fail}}$. The performance of the optimization then depends on the rate-distortion curve for the JPEG coder. The rate-distortion curve for the JPEG coder is found by measuring the distortion for different values of the quantization parameter Q. As with the sensitivity curve, the rate-distortion curve can be fit with an exponential model to provide analytical expressions for end-to-end distortion.

With the characteristics of the JPEG coder considered, a source channel optimization can be performed with some choice of a channel coder. We choose to use FEC to provide error correction for this sensitive source coder. In the optimization problem given in (3), $P_{\text{fail}} = 1 - Pb^N$, where Pb is the probability of correctly decoding a block according to (6). Gradient techniques can be used to solve the optimization problem efficiently.

IV. Results

In order to demonstrate the utility and flexibility of our approach, we simulate both the distortion-based approach for progressive coders with two different channel coders and the work allows us to optimally match all of these various source and channel coders using similar optimization techniques.

A. Distortion-based Optimization

For the distortion-based optimization, we simulated various SPIHT-channel combinations for the 512x512, 8 bpp Lena image. Sensitivity parameters for the SPIHT coder were determined for a compression rate of 1 bpp.

Simulations of optimally matching the SPIHT source coder with the unequal energy BPSK symbols channel coder (SPIHT-B) were performed for various values of P_{tot}. For comparison with this coder, we simulated a non-optimized system (CBER) that adjusts its source bitrate R_s to achieve a desired BER of 10^{-4} for all values of P_{tot}. All the simulation results are provided in terms of PSNR $(dB) = 10\log(\frac{255^2}{MSE})$ for the maximum rate R_{tot} of 1 bpp.

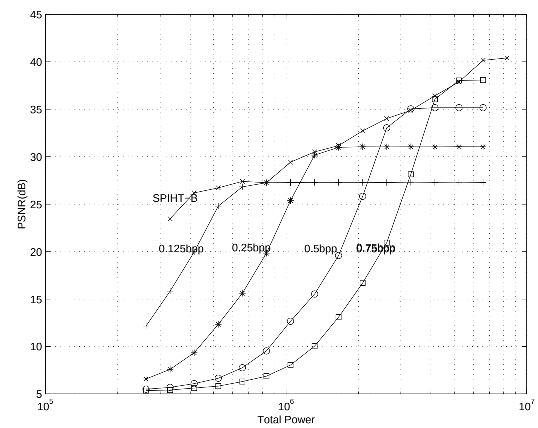

Figure 3: Simulation Results for Lena using SPIHT source and Power constrained channel for a maximum rate of 1 bpp: (a) SPIHT-B (unequal energy BSPK symbols), (b) CBER (BPSK symbols w/BER 10^{-4})

Figure 3 shows that the PSNR vs P_{tot} curve is monotonically increasing with some minor discrepancies due to convergence error and simulation with not enough trials.

Simulations of the SPIHT, RS source-channel coder combination with constant T simplification (SPIHT-R) were performed for various values of BER. For comparison with this coder, a fixed scheme with FEC that uses the same number of protection symbols at all BERs was simulated. See Figure 4.

Figures 3 and 4 show that the SPIHT-B and SPIHT-R coders outperform the CBER and Fixed RS, respectively, over the entire range of BERs, thus demonstrating the value of optimal source-channel matching. According to the flexibility of the respective coders, the SPIHT-B coder performs better at high BERs where power allocation is important while the SPIHT-R coder performs better at low BERs where infrequent errors can be corrected using FEC. At high BERs, the RS Coder can not provide adequate error protection and

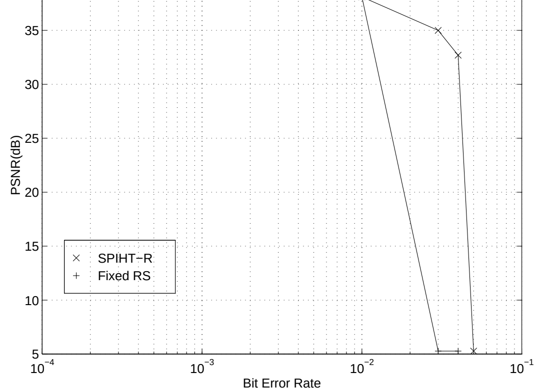

Figure 4: Simulation Results for Lena using SPIHT source and RS channel coder for a maximum rate of 1 bpp: (a) SPIHT-R (SPIHT source, Reed Solomon Codes), (b) Fixed RS (SPIHT source, Fixed FEC w/RS(255,171,42))

performance degrades significantly to a PSNR of 5.28 dB. At low BERs, the SPIHT-R coder results are nearly identical to results found in current literature such as [3] on fully joint source channel optimizations. This suggests 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.

B. JPEG Source Coder

For the JPEG, RS source-channel coder (JPEG-R) combination, analytical simulations were performed using the rate distortion curve of the Lena image over various values of P_{fail}. These analytical results provide a relative idea of the performance of our algorithms based on the the accuracy of the sensitivity model.

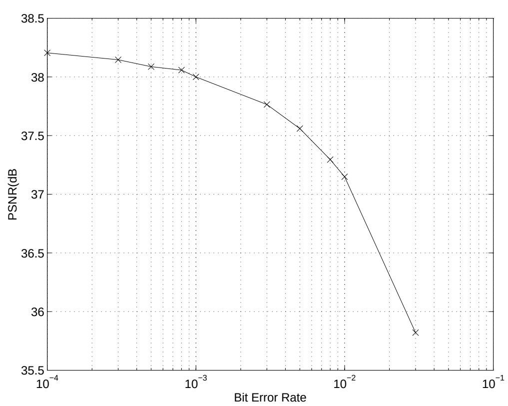

Figure 5: Analytical Simulation Results for Lena using JPEG-R (JPEG source, Reed Solomon Codes) with a P_{fail} of 10^{-3} for a maximum rate of 1 bpp

Results for JPEG-R coder show that it performs worse than the SPIHT-B and SPIHT-R coders over the entire range of BERs for the P_{fail} criterion. This result is expected JPEG coder. However, this example shows that our matching scheme optimizes performance for a variety of the source and channel coders.

V. Conclusions

We have constructed a general approach to joint source-channel matching for wireless image and video transmission. The key to this approach is the description of the end-to-end performance of the system in terms of reconstructed image or video quality at the receiver. By expressing this performance jointly in terms of the source distortion and the probability of error as related to channel characteristics, the source and channel coders can be jointly optimized to provide the best end-to-end performance. We show through the example of the SPIHT and JPEG image source coders and unequal energy BPSK channel coder and RS channel coders that efficient, general algorithms for joint optimal matching can be developed. A particular strength of our technique is that it can be applied to almost any source and channel coder combination. The example of image transmission shows that it may be possible to obtain in practice nearly all of the benefits of joint source-channel optimization by matching existing source and channel coding standards using the simple and general method proposed here.

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References

[1] J. Modestino and D. Daut, "Combined source-channel coding of images," *IEEE Transactions on Communications*, vol. COM-27, pp. 1644–1659, Nov. 1979.

[2] N. Tanabe and N. Farvardin, "Subband image coding using entropy-coded quantization over noisy channels," *IEEE Journal on Selected Areas in Communications*, vol. 10, pp. 926–942, June. 1992.

[3] G. Sherwood and K. Zeger, "Progressive image coding for noisy channels," *1997 Data Compression Conference*, p. 199, 1997.

[4] A. Said and W. Pearlman, "A new fast and efficient image codec based on set partitioning in hierarchical trees," *IEEE Trans. Circuits Syst. Video Technology*, vol. 6, pp. 243–250, June 1996.

[5] J. Shapiro, "Embedded image coding using zerotrees of wavelet coefficients," *IEEE Trans. Signal Processing, Spec. Issue Wavelets Signal Processing*, vol. 41, pp. 3445–3462, Dec. 1993.

[6] Blahut, *Digital Transmission of Information.* Addison-Wesley, 1990.