Energy Efficient Coding and Transmission

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Abstract

Efficient transmission of multimedia signals from energy limited portable devices requires a fresh look at the tradeoffs between source compression, channel coding and transmission strategies. In this paper we provide optimum operating points in terms of end-to-end source distortion and total energy consumption of the mobile due to compression, channel coding and transmission. We illustrate that the optimum strategy depends on the location of the mobile and that optimizing can prolong the battery life about ten times.

1. Introduction

Conservation of battery energy is one of the major challenges in portable information devices. The management of energy becomes even more critical with devices integrating complex video signal processing techniques with communications. Some of the key technologies that affect the battery life in this respect are source signal compression, channel error control coding and radio transmission.

Classically, source and channel coding literature and in particular joint source and channel coding techniques mainly focus on designing codes that minimize the overall distortion of the source as it travels through the channel. However, for mobile units that have limited battery capacities, overall energy consumption is also an important design factor. In this paper we incorporate the energy consumption due to transmission and due to signal processing, which includes source and channel coding, into the joint source channel coding problem and provide mathematical tools to calculate efficient operating points. Power optimization for communication systems has also been addressed in [3, 1] where specific compression and channel coding algorithms were considered. In particular [3] looked at transform coding for source compression. Our work, on the other hand, provides a general framework which can be applied to a variety of systems.

Our goal is to allocate energy between source compression, channel coding and transmission tasks to minimize the total energy dissipation while keeping the end-to-end distortion of the source constant. Alternatively, for a given total energy budget, we find the minimum total distortion that the source encounters. Bandwidth, or transmission rate is another important system parameter which affects the system performance. For the purposes of this study we assume there are no constraints on the total transmission rate, although it is possible to carry out constrained optimizations in a bandwidth limited case as well.

In this work, we will only concentrate on transmit energy, envisioning a situation such as uplink cellular communications where the base station receiver does not have power limitations. Similarly, for the downlink scenario the goal would be to minimize the receiver energy consumption. For peer-to-peer communication situations such as ad-hoc networks or cellular networks when the base station does not do transcoding, one would optimize over both the transmitter and receiver energy levels.

We consider two optimization problems: In the first scenario, we have a multitude of compression algorithms each providing a different compression rate for some fixed distortion level. Examples are vector quantizers and transform coders of fixed distortion and varying dimension. In this scenario we optimize the total energy consumption of signal processing and transmission tasks for fixed end-to-end distortion as the compressed signal travels through the channel. We illustrate how the minimum energy consumption varies with channel quality of the mobile, or its distance from the base station, and how this energy is allocated among signal processing and transmission. We also provide comparisons with the traditional case of fixed signal processing independent of channel quality. These results are presented in Section 2.

The second scenario considers a particular source coder, such as a vector quantizer of fixed dimension, with variable rate. We now fix the total energy consumed by the source compression, channel coding and transmission and minimize the end-to-end distortion. In Section 3, we examine this minimum total distortion for different channel conditions and illustrate the benefits of optimization.

2. Total energy optimization

We initially consider a simple case in which we ignore the energy consumption due to channel coding and we send source compressed bits through an additive white Gaussian noise (AWGN) channel. We assume we have access to a number of source compression techniques which provide the same source distortion with varying complexity and rate. Hence if we consider the source distortion due to compression versus the compressed bit rate, we move along the horizontal line shown in Figure 1(a). We have also plotted the operational rate-distortion curve as a reference.

The total energy consumed by the mobile at the link layer and at the physical layer consists of the energy dissipated by the source compressor E_s and the energy used to transmit the compressed bits though the channel E_t, resulting in total energy $E_{tot} = E_s + E_t$ joules. Our goal is to solve the problem

$$\text{Minimize } E_{tot} \text{ subject to } D_{tot} \leq D_0, \tag{1}$$

where D_{tot} refers to the total distortion due to source compression and channel errors. Total allowed distortion D_0 will be determined by the particular source and application at hand and will be different for telephone calls, file transfer and video conferencing. To gain insight into the solution, let us first consider a special case where we fix source distortion D_s and channel error rate individually.

Generally algorithms that compress more, resulting in a lower compressed rate for identical "quality" have higher complexity and require more processing energy. Hence for fixed source distortion D_s in Figure 1(a), the processing energy E_s is a decreasing function of the compressed bit rate R shown in Figure 1(b). On the other hand, as the number of bits representing a source letter increases, the transmitted energy per bit decreases. If we would like to keep the bit error rate of the channel constant, we need higher transmission energy E_t for larger source rates R as in Figure 1(c). Combining in Figure 1(d), we find that the total energy E_{tot} as a function of the bit rate has a minimum and the optimal operating point R^* that minimizes E_{tot} (in joules/source sample) for fixed end-to-end source distortion can be calculated.

As an example of this optimization we consider a class of transform coders of varying dimension N and squared error distortion function. We consider a first order Gauss-Markov source with variance σ^2 and autocorrelation function $c(k) = \sigma^2|\rho|^k$. The operational

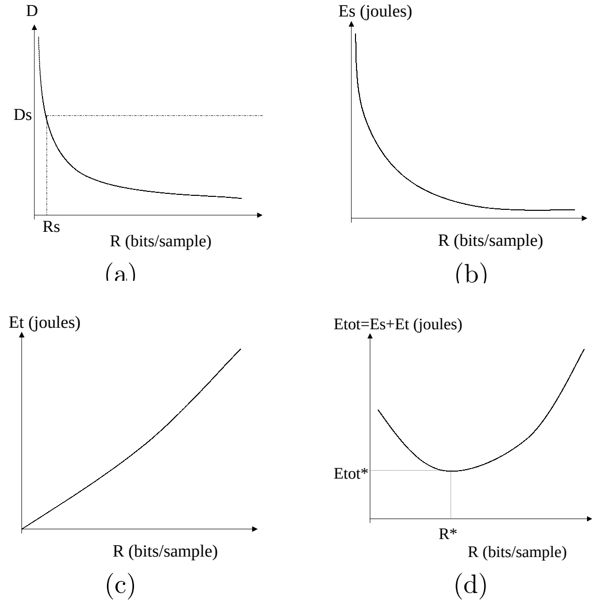

Figure 1. Minimizing total energy for fixed end-to-end distortion.

distortion-rate function of a transform coder using the optimal transform of dimension N is

$$D(R) = \epsilon\sigma^2(1-\rho^2)^{\frac{N-1}{N}} 2^{-2R} \tag{2}$$

where ϵ depends on the quantizer used for the transform coefficients [2]. Note that R is the number of bits/sample and $D(R)$ is the distortion per source sample.

We assume these source coded bits are transmitted through an AWGN channel of noise spectral density N_0 joules using differential phase shift keying (DPSK). The probability of bit error p_e is given by [5]

$$p_e = \frac{1}{2}e^{-\frac{E_t}{RN_0}}, \tag{3}$$

where E_t is the total transmit energy per source sample. Since our source is compressed using transform coding of dimension N, we will assume that N source samples (which we call a "symbol") are received correctly only when all the NR bits describing the vector are correct at the receiver. This results in the probability of symbol error p_s

$$p_s = 1 - (1-p_e)^{NR}. \tag{4}$$

Combining the effects of the source compression and channel errors, the total end-to-end distortion D_{tot} per source vector of length N can be expressed as $(1 - p_s)ND(R) + p_sN\sigma^2$ which results in per source sample distortion

$$D_{tot} = (1-p_s)D(R) + p_s\sigma^2. \tag{5}$$

Let us now turn to the calculation of total energy E_{tot}. Transforming a source vector of dimension N requires N^2 operations. Typically the number of operations necessary for the quantizer and the entropy coder following the transform is negligible with respect to N^2. Assuming the energy dissipated is proportional to complexity, with proportionality constant c_s, the energy requirement of the source coder per source sample is $E_s = c_s N^2/N = c_s N$.

Using equations (2), (3), (4) and (5), the transmit energy E_t per source sample required to keep the total distortion at level D_0 is given by $P_t = -RN_0 \ln(2p_e)$, with $p_e = 1 - (1 - p_s)^{1/NR}$ and

$$p_s = \frac{(D_0 - \epsilon\sigma^2(1-\rho)^{\frac{N-1}{N}} 2^{-2R})}{(\sigma^2 - \epsilon\sigma^2(1-\rho)^{\frac{N-1}{N}} 2^{-2R})} \qquad (6)$$

Thus the total energy per source sample due to signal processing and transmission is

$$E_{tot} = c_s N + (-RN_0 \ln(2p_e)), \qquad (7)$$

and the optimization in equation (1) can be carried out with respect to transform coder dimension N and compression rate R. In our formulation, the value of the constant c_s is chosen relative to the transmission energy. This value is device and implementation specific and can be determined experimentally.

Results of this optimization for $\sigma^2 = 1$, $\rho = 0.9$, $\epsilon = 1$ and total distortion $D_0 = 0.1$ are illustrated in Figure 2. Note that $D_0 = 0.1$ corresponds to a SNR value of 10 dB for the source. We have plotted both the total energy and transmit energy as a function of the transform coding dimension N. The rate R is optimized for each N and the block size N that minimizes total energy is denoted by a star. All the energies are in joules and normalized with respect to the constant c_s. Experiments [4] suggest that E_s and E_t are comparable, so we have chosen c_s/N_0 in the range 10-0.1.

In Figure 2(a), we consider $c_s/N_0 = 10$, modeling a scenario in which the noise power spectral density N_0, or equivalently channel attenuation, is low. We observe that as the transform coding dimension N increases, the total energy and signal processing energy, which is the difference between total energy and transmit energy, increases. The optimal N in this case is equal to 1 and results in source coding rate $R = 2$ bits/sample. Hence for good channel conditions, one does not need to spend a lot of energy compressing the source; low attenuation enables more source bits to be transmitted through the channel.

Figure 2(b) shows total energy and transmit power for $c_s/N_0 = 0.1$, where now the noise level is higher. The optimum source coding dimension N is 5 and the

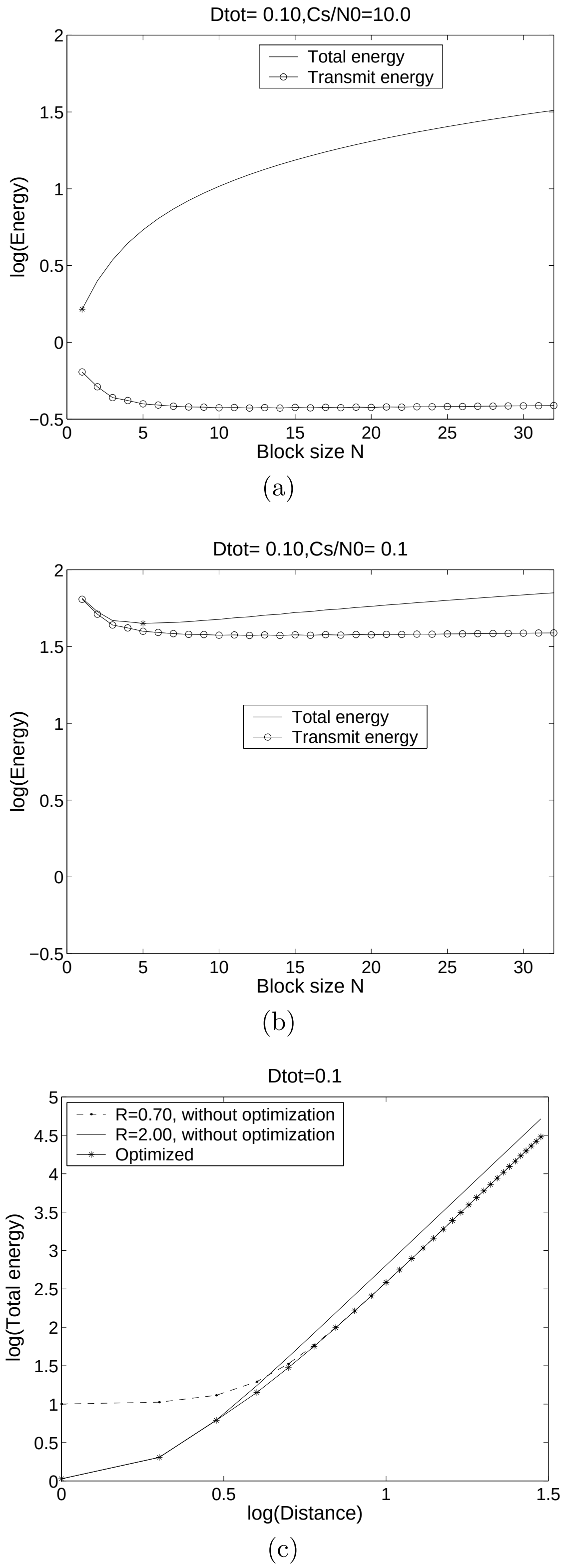

Figure 2. Total energy minimization for transform coding. The energies (in joules) are normalized to c_s.

corresponding rate R is 0.8. Since the channel attenuation is high, we need to compress the source symbols more to send them reliably through the channel.

Channel quality, or the level of noise power can also be interpreted in terms of the distance of the mobile to the transmitter. The bit error rate p_e of the DPSK modulation in equation (3) depends on the received signal to noise ratio E_t/RN_0. Since the received energy is proportional to $E_{tx}d^{-\alpha}$ where E_{tx} is the transmitted energy, d is the distance between the mobile and the base station and the exponent α depends on the propagation medium, received signal to noise ratio is proportional to E_{tx}/RN_0d^{α}. Thus, in Figure 2(a) and (b), different noise powers can also be interpreted as different distances. When the mobile is close to the base station, that is when d is small resulting in small effective noise power, the best strategy is to compress less and focus on transmission instead. However, when the mobile gets further away from the base station, more effort needs to be spent on compression as it is relatively expensive to send each bit through the channel. The level of compression to minimize total energy consumption is therefore *location dependent*.

Figure 2(c) summarizes minimum total energy consumption as a function of the distance of the mobile from the base station. The propagation exponent is $\alpha = 4$. This optimization requires that the compression and transmission strategies be adapted to the distance. On the same plot we also show two scenarios in which not only the overall distortion is kept constant at $D_0 = 0.1$ but the compression algorithm is also fixed. Then in order to keep the channel error rate constant the transmit energy per sample E_t increases with distance. As expected, fixed high compression rate ($R = 2$) performs well for small distances, but requires considerably more total energy, a factor of 2, than the optimized case for large distances. Conversely, a low compression rate algorithm ($R = 0.7$) is better suited for large distances, and the total energy dissipation is almost 10 times larger than the optimized scenario for small distances from the base station.

3. Minimization of end-to-end distortion

In this section we consider a scenario where the mobile transmitter doesn't have the flexibility of choosing among different source coders, such as different transform coders, and works with a single source compression technique. Then changing the compression rate forces the distortion to follow the operational rate-distortion curve of the source coder at hand. Thus as the compression rate increases, the distortion decreases as shown by a sample rate-distortion function in Figure 1(a).

For this scenario, we assume that total energy consumption per source letter is fixed at E_0 joules and we optimize end-to-end distortion. Again for simplicity, we will qualitatively describe an uncoded case although our numerical optimizations will include channel coding as well. We would like to solve

$$\text{Minimize } D_{tot} \text{ subject to } E_{tot} \leq E_0. \qquad (8)$$

Since the source coder follows the operational rate-distortion curve, lower distortion implies higher rate and higher processing energy. Thus source coding energy E_s per source sample increases with R. As the total energy $E_{tot} = E_s + E_t$ is fixed, the remaining transmit energy E_t joules/sample decreases with source coding rate R. In return, probability of channel errors, which is an decreasing function of E_t, increases with R. Combined total distortion D_{tot} that the source encounters as it passes through the compressor and the channel is given by equation (5), which implies that D_{tot} should have a minimum with respect to the compression rate R.

In order to illustrate the minimization in (8), we consider independent and identically distributed samples of a Gaussian source with variance σ^2. We assume this source is compressed using a mean squared error optimal scalar quantizer and then channel coded using Reed-Solomon (RS) coding. The coded bits are transmitted through an AWGN channel of noise power spectral density N_0 joules using DPSK modulation. We will include both source coder and channel coder energy consumptions as well as transmit energy in our formulation.

We first calculate total distortion. Using the high rate approximation, the source distortion for compression rate R bits/sample is $D_s = \epsilon\sigma^2 2^{-2R}$ [2], where ϵ depends on the quantizer.

The RS code maps $k = n - 2t$ information symbols to a block of n symbols where $n = 2^m - 1$. Each symbol comes from a 2^m-ary alphabet and t denotes the number of errors that can be corrected. When DPSK modulation is used to transmit R bits/source sample with transmit energy E_t joules/sample, a modification of (3) gives bit error rate $p_e = 1/2e^{-kE_t/nRN_0}$.

The RS code first maps m bits into one symbol, resulting in symbol error probability $p_{se} = 1-(1-p_e)^m$. Probability of error per block of RS code, that is per km information bits, is then

$$p_{be} = \sum_{i=t+1}^{n} \binom{n}{i} p_{se}^i (1 - p_{se})^{n-i}. \qquad (9)$$

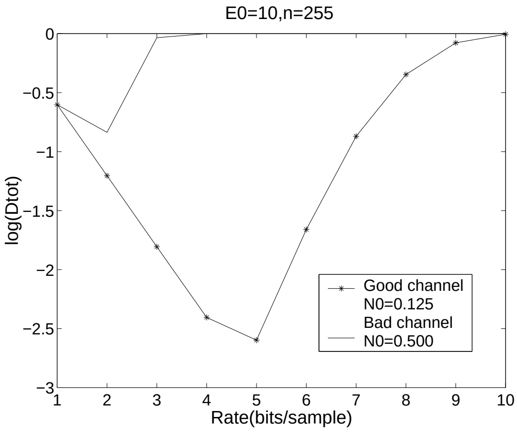

Figure 3. Total distortion minimization for scalar quantization. The total energy E_0 and noise spectral density N_0 are normalized.

Combining, the total distortion per source sample is

$$D_{tot} = \frac{R}{km}\left\{(1-p_{be})\frac{km}{R}\sigma^2 2^{-2R} + p_{be}\frac{km}{R}\sigma^2\right\}$$
$$= (1-p_{be})\sigma^2 2^{-2R} + p_{be}\sigma^2. \quad (10)$$

Note that one RS block contains km/R source samples.

The complexity of the source coder is proportional to rate R when we use a bi-section search algorithm [2], which results in source coding energy $E_s = c_s R$, where c_s is a constant. Systematic RS channel code only requires computations for the $2t$ parity symbols. In order to calculate each parity, we need one operation (multiplication and addition) per information symbol, resulting in a total of $2kt$ operations. Therefore, channel coding energy consumption per source sample E_c in terms of the constant c_c is given by

$$E_c = c_c \frac{2kt}{km/R} = c_c \frac{2Rt}{m}. \quad (11)$$

Similar to Section 2, the values of the constants c_s and c_c are experimentally determined relative to the transmit energy.

As the total energy is fixed at E_0 joules/sample, this leaves $E_t = E_0 - E_s - E_c$ for transmission. Notice that E_t is a function of RS code parameters $n = 2^m - 1$, $t = (n-k)/2$ and R. Similarly, total distortion D_{tot} in (10) is a function of the same parameters. Thus, we can minimize D_{tot} over all choices of n, t and R.

This minimization has been carried out for $\sigma^2 = 1$, $\epsilon = 1$, $E_0 = 10$, $n = 255$, $c_c = c_s = 0.25$, $N_0 = 0.5$ and 0.125. The numerical values of E_0, N_0, c_s and c_c are chosen to result in realistic bit error rates p_e and total distortions D_{tot}. Our results are shown in Figure 3. We have optimized over t, the error correction capability of the RS code, for each source compression rate R. The vertical axis denotes the total distortion. We observe that similar to the scenario in Section 2, as the channel quality degrades optimum source coding rate becomes smaller. However, in contrast to Section 2, smaller source rate implies lower source coding energy. This leaves more of the constant energy budget for transmitting through the channel whose attenuation is large.

4. Conclusions

This paper provides an analytical framework for optimizing end-to-end distortion and total energy consumption of a mobile transmitter. The total energy incorporates the source compressor, channel coder and transmitter energy. We observe that optimum distortion-energy operating points are location dependent. When the mobile is far away from the base station, or when the channel quality is bad, the optimum strategy is to have a low compression rate since it is quite expensive to transmit each compressed bit. Conversely, good channel quality enables the transmitter to have minimal amount of compression and transmit at a relatively high rate.

Although this paper mainly focused on transmit energy, other scenarios include optimizing the receiver energy consumption (for cellular downlink) or optimizing transmit and receive energies jointly (for peer-to-peer communications, or for no base station transcoding). At the transmitter the source coder dissipates most of the signal processing energy, whereas at the receiver channel decoder is the bottleneck. Another possible extension is to multiuser scenarios, where interference from nearby users affects the channel error rate of the mobile and the total available bandwidth has to be shared among the different users.

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