ADAPTIVE LOW POWER MULTIMEDIA WIRELESS COMMUNICATIONS

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Abstract - In this paper, we introduce a novel approach for adaptive minimization of the *total energy consumption* in multimedia wireless communications subject to achieving a given quality of service. Our approach exploits trade-offs between the effects of energy consumed in processing (source and channel coding) and energy consumed in transmission under different noise and channel conditions, on the received quality of the multimedia. We present several simulation results involving image transmission that illustrate the energy consumption savings that can be achieved using our proposed approach.

INTRODUCTION

Wireless multimedia services will play an increasingly important role in society. Mobile communications and computation platforms must rely on batteries for their operation. Unlike other enabling technologies for mobile information systems, the specific energy of commercially available rechargeable batteries has improved at only about 2 percent per year over the past half century. Since frequent recharging is not a practical option and low weight is crucial in wireless equipment, wireless multimedia systems will have to be *optimized for low energy consumption subject to a desired quality of service.*

In conventional wireless communications coding scheme, the data compression rate for a particular media is fixed and set to provide acceptable perception quality. High compression rate coders are used to optimize the utilization of the available channel bandwidth. Compressed data can be transmitted faster and therefore can lead to an overall reduction of total consumed transmission energy. Further, some of the bandwidth saved by compression can be used to add error correction bits. With error correction coding, one can further reduce transmission power with no reduction in the quality of service. However, efficient encoding comes at a price: computational complexity and sensitivity to channel mismatch. A high compression rate coder consumes more battery energy, and requires more protection to combat channel mismatch.

Processing energy consumption: Intuitively, one expects compression efficiency to be proportional to coding complexity, i.e. processing energy consumption is inversely proportional to the data rate. In other word, the computation complexity of a low efficiency coder that yields high data rates should

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be lower than that of a more efficient coder that achieves lower data rates. We will refer to this kind of characteristic as the *inverse complexity-rate* rule. For example, the MPEG standard, or any video coding standard which requires motion estimation (ME) can be made to follow that rule, by adjusting number of prediction frame (more ME or less). Since ME takes considerable computation time [1]. On the other hand, most image compression algorithms do not obey the inverse complexity-rate rule. For example, higher compression rate in JPEG do not require more operations than lower compression rates.

Transmission energy consumption: The choice of data modulation scheme is dictated by the constraints that the communications system has to satisfy. The general principle is that the more data we have to transmit the more energy or power will consume. Transmission can be accomplished either using multilevel modulation scheme (e.g., 64-QAM, power oriented), or fixed modulation scheme with increased bandwidth or non real-time mode (sending out data in a longer time, energy oriented).

With the above remarks in mind, we may capture the energy consumption of any communication system with the help of the curves shown in Figure (1). For example, Fig. (1.a) shows the trade-offs between processing and transmission energy consumption as a function of data rate for a given BER. Figure (1.c) shows an end-to-end distortion surface as a function of data rate and BER. Combining fig. (1.a) and fig. (1.c) we can then construct iso-distortion (equal end-to-end distortion) energy-rate curves (Fig. (1.d)). Note that transmission-energy-rate curves are not fixed: they depend on channel noise levels and the target quality of information.

Previous researchers have focused on power or energy minimization in two areas: 1. global interference minimization, by Zander [2], and 2. low power VLSI design, e.g. [3]. To our knowledge, this is the first attempt to take an integrated view of energy minimization in multimedia wireless transmission based on the optimization of the source/channel coding algorithms, modulation schemes and transmission power levels.

TOTAL CONSUMED ENERGY MINIMIZATION

We may capture the energy consumption of communications systems using the generalized total energy consumption equation:

$$E_{tot} = f(R_t(R_b + R_c), N, d_r). \tag{1}$$

Here d_r is the end-to-end distortion, R_t is the total transmission rate, R_b is the compressed data rate, R_c is the error correcting code rate, N is the noise power density, E_{tot} is the total energy consumed for the whole system. Our goal is to use R_b to solve the following optimization problem: *For a given end-to-end distortion, noise power in the channel, and a transmission rate, which* R_b *will minimize total energy consumption?* The generalized total energy consumption equation is highly system dependent (source coding, channel coding, VLSI implementation, and transmitter design) and complicated due to the integration of coding schemes and modulation. Thus, we choose the following example to illustrate problem and equation formulation.

Problem formulation: a DCT based coding example. Here we use different DCT block size to vary the compression rate. We will present a generalized processing energy equation ($E_{proc}(R_{b_N})$), and equations to find the transmission power requirement (in terms of M-level modulation and error bit rate (BER)). The estimate of energy consumption for an image coder at different block size N can be approximated by the equation, [4, 5, 6]

$$E_{proc}(N) = L^2(A \times 2\log_2 N + M) + T, \quad N = 4, 8, 16, 32, 64. \tag{2}$$

Here L is the image size, A and M are the energy consumption factors for arithmetic operations and memory accesses, respectively, and T is the energy consumption due to modulation process, and error correction processing. We assume that T does not depend on the bit rate. Let us relate this equation to the real coding rate through the distortion-rate equation. Assuming that the transformed source is a Gaussian source, the distortion-rate equation can be expressed as the follow:

$$d_q = 2^{-2R_{b_N}} \sigma_N^2, \qquad N = 4, 8, 16, 32, 64. \tag{3}$$

Here, σ_N^2 is the variance of scaled transformed coefficients of block size N. As N increases we expect a more compact representation of the data in the transform domain. Therefore σ_N^2 tends to be smaller. Now let us assume that $\sigma_N^2 = K/\sqrt{\log_2 N}$, where K is a constant depending on the source distribution [6]. Substituting the above equation and eq. (3) in eq. (2), we obtain

$$E_{proc}(R_{b_N}) = L^2(2A(2^{-2R_{b_N}} K/d_q)^2 + M) + T, \tag{4}$$

where d_q is given in eq. (3) and $N = 4, 8, 16, 32, 64$. The end-to-end distortion for the entire communications system consists of two parts: quantization distortion (d_q) and channel distortion (d_c). The channel distortion equation is very complicated. To simplify the problem, we can set a threshold channel distortion value, and find the corresponding BER requirement. Since the dynamic range of transformed coefficients for a block size N is about twice as much as for a block size $N/2$, the BER requirement for the block size N should be half of the block size $N/2$. For a channel distortion close to 10% of quantization distortion, we have a BER, P_b, equal to $10^{-3}, 5e10^{-4}, 2.5e10^{-4}, 10^{-4}, 5e10^{-5}$ for $N = 4, 8, 16, 32, 64$ respectively [7]. For an additive white Gaussian noise channel (AWGN) an efficient modulation scheme as M-QAM can be used. Its performance can be approximated by [7],

$$P_c(M, \gamma_c) = \frac{\sqrt{M} - 1}{(\sqrt{M} log_2 \sqrt{M})} erfc \sqrt{\frac{3\gamma_c}{2(M-1)}}. \tag{5}$$

Here, P_c is the channel BER, γ_c is the transmission power to noise power ratio, C/N_o, and *erfc* is the complementary error function.

If the channel coding is used in communications system, e.g. BCH coding, then we can relate the input and the output error probability by [7]:

$$P_b(t) = \frac{1}{n} \sum_{j=t+1}^{n} j \binom{n}{j} P_c^j (1 - P_c)^{n-j}, \tag{6}$$

where n is the total bits in a block, t is the maximum correctable bits.

Note that there is no analytical way to express γ_c in term of P_b through eq. (5) and eq. (6). Therefore, we cannot find an analytical solution for E_{tot}. However, since we use discrete bit rate and P_b values, eqs. (5) and (6) can be solved in a table form for on-line processing.

Adaptive algorithm: Figure (3) shows the block diagram of the *on-line* procedure used by an adaptive low power multimedia wireless communications. The energy saving algorithm works as follows:

1. Determine the channel information (noise level, etc), and the target quality of service (distortion, etc) which yields R_b (e.g., using eq. (3)) and R_c. Update transmission power requirements for each bit rate (e.g., using eq. (5) and eq. (6)). Given an estimate of transmission time (since we know the rates), this also yields a transmission energy table.
2. Add the resulting transmission energy table to the pre-stored processing energy table (e.g., using eq. (4)) and find the minimum total consumed energy.
3. Code the input data at the rate determined above and with the error correction procedure selected above. Send the state information through a control channel for rate setting.
4. After a pre-established interval, go to step 1.

Note that this algorithm is very simple to implement. A little overhead processing power is required for such computation.

NUMERICAL EXAMPLES

Fixed bit rate example using the DCT: Suppose that we want to transmit the image Lena256x256 (from the USC database) at a fixed bit rate $(R_b + R_c)$. In this case minimizing energy is equivalent to minimizing power.
Step 1. Let us set the quantization distortion to 30. From eq. (3) we get R_{b_N}=1.7 1.5 1.36 1.2 1.05 bpp, for Lena image. If BCH coding (n=63, k=57,51, 45,39,36, t=1,...,5, k is the information bits) is used to pad different coding rates, more compressed data can be protected better. Let the overall rate be close to 1.9 bpp. Using the P_b from above discussion, we find a set of possible P_c values which we store in a vector, $\vec{P_c}$. Now let us find γ_c in (5) to satisfy $\vec{P_c}$. For M=16, we found the corresponding γ_c, Γ_c, as [34.67 28.84 24.54 21.87 19.95]. We can also express Γ_c in terms of the transmission power C, i.e. $\vec{C} = \Gamma_c N_o$.
Step 2. Let us set t_{proc} (average processing time) to one second for all rates. Adding $\vec{C}$ to the corresponding processing power, $\vec{P}_{proc} = \vec{E}_{proc}/t_{proc}$, for R_{b_N}=[1.7 1.5 1.36 1.2 1.05], $A = 900$, $M = 4200$, $T = 1000$ (pico Joule), we get the total consumed power set, $\vec{P}_{tot} = [34.67N_o{+}0.51,\ 28.84N_o{+}0.63,\ 24.54N_o{+}0.75,\ 21.87N_o + 0.86,\ 19.95N_o + 0.98]$. Note that the power is a function of noise level (N_o). Figure (2.b) shows how rate choice is determined by noise power levels for minimum energy consumption.

Variable bit rate example: Let us use a notebook computer to transmit Lena image over a wireless channel. Here we assume that there is no real-time constraint, hence the total bit rate is not fixed. Let us suppose the modulation scheme used by the notebook computer is 16 QAM. Thus, we have to minimize the total energy consumption. The notebook has two image compression tools, JPEG and SPIHT [8].

To have a good visual image quality, we set the end-to-end image distortion to a PSNR value of 35 dB. SPIHT image coder is a more efficient coder compared to the JPEG coder. However, SPIHT coded images are very vulnerable to communication channel mismatch. To maintain the quality of service (PSNR=35dB), we require the BER for SPIHT coded image to be less than 10^{-7} (fig. (4)), and the BER for JPEG to be less than 10^{-5} (fig. (5)). To achieve such low BER we applied BCH error correcting code (we could use other codes, but BCH code is simple and widely used block code) to the coded images. Based on the above requirements, we ran our simulation by sending coded images over an AWGN channel under different noise power levels. The total consumed energy for each simulation result is presented at figure (6). Figure (7) presents the minimum consumed energy for the proposed method for various noise levels. Note that for bit rate below 1.5 bpp the SPIHT coder (image coded at 0.8 bpp) is used with different error correction capabilities of BCH coding. For the bit rates 1.5 and 1.7 we used JPEG coder (1.4 bpp) with BCH coding (63 57 1) and (63 51 2) respectively, to achieve required BER.

The results that we have obtained in this case indicate that the system should use the following rules to minimize energy consumption. 1. If the noise power is under 7mW, select JPEG coder with BCH code (63 57 1). 2. If the noise power is above 7mW, always select SPIHT coder with combinations of BCH coding. It is very interesting to observe the results in the sense that for a low transmission power wireless network (pico-cell), it is better to use less efficient source coder, such as JPEG. However, for a medium transmission power network (micro-cell), depending on noise power levels, an efficient coder with smart choice of channel coding will determine minimum energy consumption.

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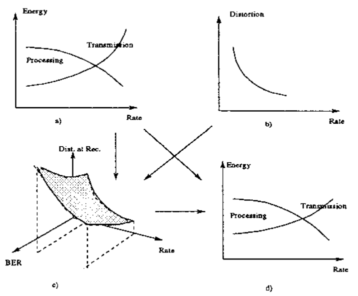

Figure 1: Graphic interpretation of Energy-rate curve. a) Generalized Energy-rate curve. b) distortion-rate curve. c) 3D plot of end-to-end distortion, channel error (BER), and data rate. d) Iso-distortion Energy-Rate curve.

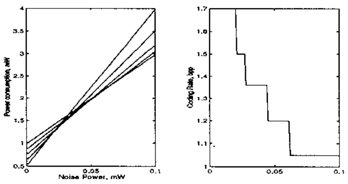

Figure 2: Left figure: total power consumption. The curves represent for each different coding rates, reading from top to bottom as 1.7 1.5 1.36 1.2 1.05 bpp. Right figure: Rate requirement for minimum total power consumption under different noise levels.

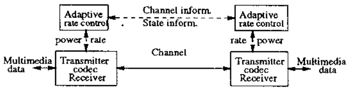

Figure 3: Adaptive low power multimedia wireless communications.

Figure 4: SPIHT coded Lena at 0.8 bpp.

Figure 5: JPEG coded Lena at 1.4 bpp.

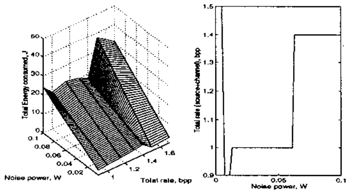

Figure 6: Left figure: Total energy consumption surface. Right figure: Rate requirement for minimum total energy consumption under different noise levels

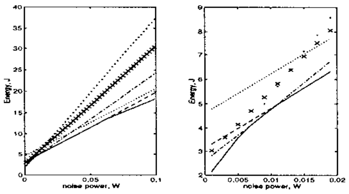

Figure 7: Left figure: Total energy consumption, '-.' 0.9 bpp, '–' 1 bpp, ':' 1.3 bpp, '.' 1.5 bpp, 'x' 1.7 bpp, '-' optimum rate choices. Right figure: Zoom-in version of left figure