Unequal Power Allocation for JPEG Transmission Over MIMO Systems

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***Abstract*—With the introduction of multiple transmit and receive antennas in next generation wireless systems, real-time image and video communication are expected to become quite common, since very high data rates will become available along with improved data reliability. New joint transmission and coding schemes that explore advantages of multiple antenna systems matched with source statistics are expected to be developed. *Based on this idea, we present an unequal power allocation scheme for transmission of JPEG compressed images over multiple-input multiple-output systems employing spatial multiplexing.* The JPEG-compressed image is divided into different quality layers, and different layers are transmitted simultaneously from different transmit antennas using unequal transmit power, with a constraint on the total transmit power during any symbol period. Results show that our unequal power allocation scheme provides significant image quality improvement as compared to different equal power allocations schemes, with the peak-signal-to-noise-ratio gain as high as 14 dB at low signal-to-noise-ratios.**

***Index Terms*—Distortion model, joint source-channel coding, JPEG, multiple-input multiple-output systems, unequal error protection, unequal power allocation.**

I. Introduction

IMAGE and video communication is becoming very common in wireless cellular systems with the introduction of high data rates and efficient coding schemes. It is highly anticipated that with the implementation of multiple-input multiple-output (MIMO) systems, real-time image and video communication will be among the major applications of next generation wireless systems. An important characteristic of most of the current image and video coding standards is that of unequal importance of data. In almost all the current image and video coding standards, data layers with unequal contribution to image quality can be created. This property of unequal importance and layering of data can be used to design efficient coding and transmission schemes that take into account image and video statistics. This idea has been a focus of active research over the past few years and many joint coding and transmission techniques have been developed. These methods are commonly known as joint source-channel coding (JSCC), and joint source coding and transmission power allocation depending on the type of joint design. The main idea behind these joint design techniques [1]–[4] is to allocate the available resources in such a way that more important data suffer less distortion at the cost of more distortion for less important data, with the goal of minimizing overall distortion in the received images and videos. These resources can be source and channel coding bits, total transmission power, delay, etc. By using such joint design techniques, significant quality gains can be achieved without violating constraints on different available resources.

JSCC is the most commonly studied joint design problem for image and video communication in the literature. Another important joint design problem is that of transmission power allocation and optimization for image and video communication. The main goal for such problems is either to minimize the total distortion with a constraint on available transmission power, or to minimize the power usage with a constraint on maximum "tolerable" distortion. In Section I-A, we discuss various existing joint design methods for efficient image and video communication.

A. Background

In [5] and [6], Modestino *et al.* proposed JSCC methods for digital images. In these methods, distortion in the form of mean-squared-error (MSE) was computed using the probability density functions of the coded source, the quantizer step size and the channel probability of error. Most important bits were protected using selective error protection. These methods demonstrated that significant increase in image quality could be achieved using efficient channel coding without imposing any penalty on the transmission bandwidth. In [7], Chande and Farvardin proposed a JSCC scheme for progressive image transmission over noisy channels. They developed algorithms for optimal allocation of source and channel coding bits using average distortion (MSE), average peak-signal-to-noise ratio (PSNR) and average useful source coding rate as the cost functions. In [8], Sherwood and Zeger proposed an efficient method for progressively coded image transmission using concatenated channel codes.

In [9], Eisenberg *et al.* presented a transmit power management scheme for transmission of compressed video sequences over a wireless channel. The energy needed to transmit the video was minimized under a delay and distortion constraint.

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To achieve this, the source coding and physical layer parameters were adjusted simultaneously. Their results showed that its is more energy efficient to jointly optimize the source coding parameters and transmission power than adjusting them independently. In [10], Atzori presented a method for unequal power distribution among different JPEG2000 coding units based on their contribution to total image quality. In this scheme, the JPEG2000 stream was divided into different coding packet groups. These different groups were transmitted through separate subchannels and different rate and power. This scheme showed a PSNR gain of around 4 dB at low SNRs for additive white Gaussian noise (AWGN) and Rayleigh fading channels as compared to equal power allocation.

In [11], Kozintsev and Ramchandran presented a multiresolution framework for optimally matching the source resolution and signal constellation resolution trees for a wavelet image decomposition based source coding model. The multiple resolutions resulting from subband decomposition of the image were mapped to the multiresolution channel codes based on instantaneous channel state information (CSI). This was achieved using a Lagrangian-based optimization formulation while keeping the transmitted modulation energy and bandwidth fixed. It was shown that using the multiresolution based approach, 2–3 dB of gain in signal-to-noise ratio (SNR) is typically achieved over source-channel optimized single resolution based approaches.

Zhang *et al.* presented a power minimized bit allocation scheme for wireless video communication in [12]. In this paper, the authors allocated the total available bits between the source and the channel coders based on wireless channel condition and video quality requirements such that the total power consumption was minimized. In [13], Yousefi'zadeh *et al.* presented a power optimization problem for wireless multimedia transmission with space-time block codes. A set of optimization problems aimed at minimizing the total power consumption with a given level of quality of service and bit budget were formulated. They used Gauss-Markov and video source models as their source coding model, Rayleigh fading channel with Bernoulli/Gilbert-Elliott loss models, and space-time codes for transmission. Their results showed that lowest optimal power values were obtained when multiple transmit and receive antennas were used.

In [14], Lu *et al.* developed a power minimization method subject to a given level of quality of service for H.263 video encoder employing Reed-Solomon channel codes for transmission. They used empirical models to estimate the distortion due to source coding and transmission errors. They minimized the total power consumption of the system consisting of power consumption by the source and the channel encoder, and the transmission power, with a constraint on total allowable distortion. Kim and Kim presented another H.263 based power optimization method for code division multiple access (CDMA) systems in [15]. In this method, a distortion model that takes motion compensation into account was developed for H.263 video data employing error concealment. This model was then used to minimize the target bit error rate (BER) of image frames such that the total consumed power is minimized with a constraint on maximum distortion. This scheme showed around 3.5 dB PSNR gain as compared to conventional schemes that use fixed target BER.

Tian presented two power allocation schemes for wireless video communication in [16]. In these schemes, distortion was minimized by allocating transmission power across packets with a constraint on total transmission power. Using these schemes, the author showed that a PSNR gain of up to 0.85 dB can be achieved as compared to constant power methods. In [17], Ji *et al.* developed a power optimization method for transmission of MPEG-4 fine granularity scalable (FGS) coded bitstream over MIMO systems employing orthogonal frequency division multiplexing (OFDM). In this method, total distortion was minimized by power-efficient assignment of scalable source to spatial subchannels with a constraint on total transmit power. Their scheme showed a PSNR gain of around 2.5 dB as compared to different nonoptimal schemes.

In [18], Luna *et al.* presented an energy efficient video transmission scheme over wireless channels with delay and quality constraints. In this method, source coding parameters were selected jointly with transmitter power and rate adaption, and packet transmission scheduling. The goal of this scheme was to transmit a video frame with minimum transmission energy under quality and delay constraints. Yu *et al.* present another interesting energy optimizing scheme for JPEG 2000 image transmission over wireless sensor networks in [19]. In this scheme the authors jointly adjusted the source coding scheme, the channel coding rate and the transmission power levels to minimize the overall processing and transmission energy with a constraint on total distortion.

In another related paper, Appadwedula *et al.* [20] presented a power optimization method for image transmission over wireless channels. In this method, the source coder, the channel coder, and power consumption were jointly optimized. They maximized image quality with total power constraint on both the RF transmission power, and the power consumption of the digital implementation of the channel coder.

A few more joint design methods (JSCC and power/energy optimization) for efficient image and video communication are discussed in [21]–[31].

B. Limitations of Existing Power Optimization Methods

The main goal of all the methods discussed above was either the minimization of energy/power with a constraint on total allowable distortion, or the minimization of distortion with a constraint on total energy/power. These methods showed large amounts of energy/power savings or quality gains as compared to methods that transmitted the images and videos with equal power. Despite significant quality gains and energy/power savings, these methods have certain limitations as discussed below.

- Most of these unequal power/energy allocation methods either used simulations or energy-distortion curves (similar to rate-distortion curves in joint source-channel coding literature) to estimate the distortion at the transmitter at various power configurations. The entire process of constructing energy-distortion curves and/or running simulations to estimate distortion increases the computational complexity of the optimization process, making it infeasible for real-time image and video transmission.

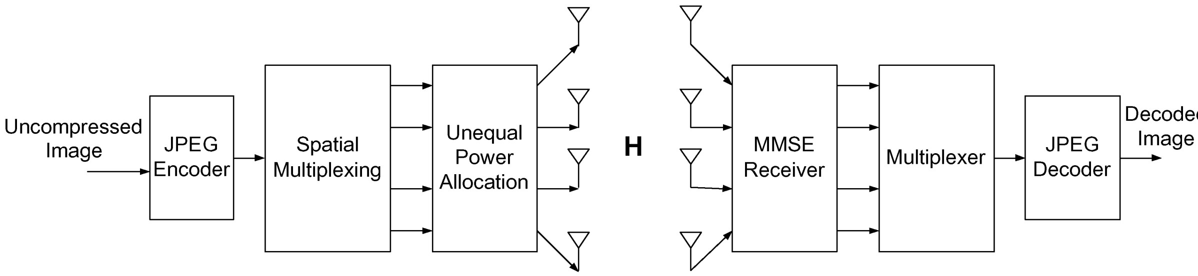

Fig. 1. System model for UPA based MIMO system for JPEG image transmission.

- Most of the unequal power/energy allocation methods for wireless image and video communication assume the channel to be constant over a packet or layer. However, in practical systems it is not necessary that the channel will remain constant during the transmission of an image or video packet or layer even for quasi-static channels. If the channel changes during a packet or layer, the distortion estimate, and, hence, the power allocation scheme would give incorrect results and, hence, large amounts of quality degradation. Due to this reason, the power allocation methods should take into account the effects of channel changes during an image/video packet or layer transmission.
- Most of the current power/energy allocation methods are either for wireline systems or wireless systems with single transmit and receive antennas. With MIMO systems expected to become an integral part of the next generation wireless systems, these power/energy allocation methods will not be very useful for image and video transmission.

C. Contribution—Unequal Power Allocation for JPEG Transmission Over MIMO Systems

MIMO systems are expected to be implemented in next generation wireless systems. With the use of multiple transmit and receive antennas and advanced coding schemes such as space-time codes, MIMO systems can be used to increase system capacity as well as data reliability in wireless communication systems [32]–[35]. Since high fidelity image and video transmission require high bandwidth and reliability, MIMO systems are highly advantageous for transmission of images and videos. Most of the research in MIMO systems and space-time codes has focused on designing codes with the goal of minimizing overall error rate and maximizing data-rate with the assumption of equal importance of data. However, as discussed above, almost all of the current image and video coding standards divide the coded images and videos into different layers with unequal importance. Therefore, to take full advantage of MIMO systems, image and video coding and transmission techniques should be designed that take into account this property of the underlying source. By designing space-time coding and transmission schemes that take into account source statistics and unequal importance of image and video data, better quality and higher data rates can be achieved without any overhead on total bandwidth or energy/power.

Based on this idea, an unequal power allocation method for transmission of JPEG compressed images over MIMO systems is proposed in this paper. The image is divided into different quality streams, and these different streams are simultaneously transmitted over different antennas with unequal power using spatial multiplexing . Transmit power is allocated between different streams with the goal of minimizing the overall distortion in the received image. The total transmit power over all the transmit antennas during any symbol period is kept constant. The effects of channel changes during an image segment/layer transmission are also taken into account in this method. Results show that quality gains as large as 14 dB in terms of PSNR are obtained at low channel SNRs. As discussed above, where a good amount of work has been done for designing unequal power allocation methods for image and video transmission over wireless systems with single transmit and receive antennas, very little research has been carried out to date for designing such methods for MIMO systems. In Section II, we present our system model. Section III formulates our unequal power allocation (UPA) problem, and provides a suboptimal solution. Section IV provides simulation details with Section V discussing our results. We conclude the paper in Section VI.

II. System Model

A block diagram of our system model is shown in Fig. 1, with a description of different components given below.

A. Source Coding Model

We used a progressive discrete cosine transform (DCT) based JPEG coder with spectral selection mode of operation [36]. The image is coded into 64 different quality layers (a DC layer and 63 AC layers), where each layer corresponds to the DCT coefficients from a particular subband. These DCT coefficients from the DC layer are encoded using differential pulse coded modulation (DPCM) coding, run-length and Huffman coding, whereas the DCT coefficients from the AC layers are encoded using run-length and Huffman coding. Within each layer, RST (reset) markers are introduced to prevent error propagation between different parts of the bitstream. Encoding and decoding are reinitialized at each RST marker. The encoded data between two consecutive RST markers in a layer is called a “segment”. More details on this source coder can be found in [37] and [38]. After coding the image in 64 layers, headers and markers are separated from the bitstream, and they are assumed to be transmitted error free since they only constitute a small portion of the bitstream [38]. At the receiver, headers and markers are re-inserted at their appropriate locations before decoding.

B. Spatial Multiplexing

After removing headers and markers, the bitstream is then passed to the spatial multiplexing (SM) block. The SM block divides this bitstream into four equal length streams, since there are four transmit antennas. Streams are formed in order of importance, with stream number 1 being the most important and stream number four being the least important. These streams are then passed to the power optimization block for unequal power allocation. At the receiver, the multiplexer/combiner combines these streams into a single stream and passes it to the JPEG decoder.

C. Channel Model

We use four transmit and four receive antennas in our MIMO system for transmission of JPEG compressed bitstream. We assume that the channel is Rayleigh flat fading with a slow fading model. The channel matrix $\mathbf{H}$ is a 4×4 matrix whose entries form an i.i.d. Gaussian collection with zero-mean, independent real and imaginary parts, each with variance 1/2. We assume that the channel $\mathbf{H}$ is perfectly known both to the transmitter and the receiver. This is a common assumption in literature and there exist many schemes that estimate channel with reasonable to high accuracy [39], [40]. Four-quadrature amplitude modulation (4-QAM) is used for modulating the bitstream.

D. Power Optimization

The power optimization (PO) block divides the 4 streams into nonoverlapping blocks of lengths $2 \times T$ bits ($4 \times 2T$ matrix), where T is the number of symbols for which we assume the channel to be constant, and 2 is the number of bits per symbol for 4-QAM modulation. Note that we will use the term block in this paper to refer to a block (containing four streams) of symbols over which the channel is constant. Power optimization is then performed over each of these blocks independently to allocate transmit power between different streams such that the overall distortion in the image due to each block is minimized. The distortion model originally presented in [37] and [38] and modified in Section III-B is used to determine minimum distortion. The total transmit power from all the antennas during each symbol period is kept constant at any given instant. The power optimization block is also responsible for modulation and assigning different streams to different antennas. Antenna assignment is performed by a simple antenna selection method during power optimization, as described in Section III-C.

E. MMSE Receiver

We used a minimum mean-squared error (MMSE) receiver to decode the spatially multiplexed bitstream. The MMSE receiver is a linear receiver, i.e., it separates the transmitted data streams and then independently decodes each stream. More details on the MMSE receiver for spatial multiplexing systems can be found in [41].

Notation

Let N be the total number of $4 \times 2T$ blocks in the image stream, and $\mathrm{x}_n = [x_{1,n}\ x_{2,n}\ x_{3,n}\ x_{4,n}]^T$ be the transmit power vector for block number n, with the elements of the vector corresponding to streams 1 to 4, respectively. Without loss of generality, the symbol period can be normalized to 1 to simplify the relationship between transmit power and energy. Also, it can be assumed that the noise covariance matrix is the Identity matrix $\mathbf{I}_4$. Hence, the transmit power is equal to signal-to-noise ratio (SNR) per symbol E_s/N_0 during any symbol period. Let $\mathbf{X}_n$ be a diagonal matrix with the k^{th} element of x_n as the $(k,k)^{th}$ entry of $\mathbf{X}_n$. Similarly, let $\overline{\mathbf{X}}_n$ be a diagonal matrix containing the square root of the entries of $\mathbf{X_n}$. Then, the received signal vector can be written as

$$\mathbf{y} = \mathbf{H}\overline{\mathbf{X}}_n\mathbf{s} + \mathbf{n}$$

where $\mathbf{y}$ is the received 4×1 signal vector, $\mathbf{s}$ is the 4×1 transmit signal vector, and $\mathbf{n}$ is the 4×1 zero mean circularly symmetric complex Gaussian noise vector with covariance matrix $\mathbf{I}_4$.

III. Unequal Power Allocation

Since different streams in the compressed image have different importance to image quality, more important streams should be transmitted with more protection from errors as compared to less important streams. One way to achieve this is to transmit different streams with unequal transmit power with more important streams being transmitted with more power and less important streams with lesser power, without violating the total transmit power constraint. In this section we present our unequal power allocation method for transmission of different streams in a JPEG compressed image over MIMO systems. The main goal of this method is to transmit different streams from different antennas with unequal power such that overall distortion due to each block in the transmitted image is minimized. The total transmit power over all the antennas is kept constant during each symbol period. In this section, first we briefly discuss our notation, and formulate the power allocation problem. We then present our modified distortion model for estimating distortion, and propose a suboptimal numerical solution to the optimization problem.

A. Problem Formulation

The goal of the UPA problem is to find the optimal x_n that minimizes the distortion in the image due to block number n. In this section, the UPA problem is formulated as a constrained minimization, where the objective is to minimize the MSE in the received image due to block n, with an equality constraint on transmit power. This minimization is carried out over all the blocks independently. The total MSE in the image is the sum of MSE due to all the blocks: $MSE_T = \sum_{n=1}^{N} MSE_n(\mathbf{x}_n)$, where N is the total number of blocks and $MSE_n(x_n)$ is the MSE contribution in the image due to block n. Since the MSE due to the individual layers and segments is additive [37], [38], the MSE due to individual streams is also additive because different streams contain data from different layers. Hence, the MSE in the image due to block n can be written as

$$MSE_n(\mathbf{x}_n) = \sum_{k=1}^{4} MSE_{k,n}(x_{k,n}) \tag{1}$$

where $MSE_{k,n}(x_{k,n})$ is the MSE due to the k^{th} stream in the n^{th} block. The MSE is minimized for each block independently due to the additivity of the MSE's from individual blocks as discussed in Section III-B. Hence, for block n, our optimization problem can be stated as

$$\min_{\mathbf{x}_n} MSE_n(\mathbf{x}_n) \tag{2}$$

with the equality constraint

$$g(\mathbf{x}_n) = \sum_{k=1}^{4} x_{k,n} = P_{\mathrm{TOT}} \tag{3}$$

where P_{TOT} is the total transmit power from all the antennas at any given instant. Note that $E_s = P_{\mathrm{TOT}}$ in our case since the symbol period is 1. Once a value of $x_{k,n}$ is obtained, the entire k^{th} stream in the n^{th} block is transmitted with power $x_{k,n}$.

B. MSE Estimation

A main part of the minimization problem in (2) is to find $MSE_{k,n}(x_{k,n})$ for different values of $x_{k,n}$ in real-time during the optimization procedure. One way of achieving this is to introduce random bit errors in the coded image, decode it and then find the MSE by comparing the corrupted image to the original image. While this method will give an accurate estimation of the MSE, it is highly computationally intensive and, hence, not feasible in practical real-time optimization methods. A computationally efficient method is to use some kind of distortion model to predict the amount of the MSE at different source coding rates and channel bit error rates, and then use this model to estimate the MSE in (2). In our previous work in [37] and [38], we developed a distortion model for predicting the MSE as a function of source coding rate and channel bit error rate (BER) over a set of images. In this paper, the distortion model is modified to work on a per-image basis rather than a set of images, and use it to predict MSE in the image due to individual streams and blocks. By "per-image" we mean that only the information from the current image is used to evaluate MSE. Note that a block contains 4 streams, and each stream in a block can have one or more full or partial segments of the JPEG stream. Each segment can either contain coded DC coefficients or coded AC coefficients. MSE expressions for DC and AC segments were derived in [37] and [38] for a set if images. We modify these expressions to work on "per-image" basis so that power optimization can be performed for an image in real-time.

Suppose a segment s is divided into V nonoverlapping partitions. This case arises when a segment is transmitted over multiple blocks. Let M be the number of coefficients in each segment of an image (a constant) and let $M_{s,v}$ be the number of coded coefficients in partition v of segment s. Suppose the first bit error in segment s occurs at bit number $i_{s,v}$ corrupting all the $m_{s,v}$ coded coefficients from this point to the end of the segment. Let $\mu_{u,s}$, $\mu_{\xi,s}$, $\sigma^2_{u,s}$, and $\sigma^2_{\xi,s}$ be the unquantized coefficient mean, quantization error mean, unquantized coefficient variance and quantization error variance for the coefficients in segment s of the image. Let $p^e_{s,v}$ be the probability of bit error in partition v of segment s, and $p^e_{s,t}$ be the probability of bit error for the t^{th} partition of segment s. Also, let $w_{s,t}$ and $w_{s,v}$ be the number of bits in the t^{th} and v^{th} partitions respectively, and N be the total number of pixels in the image. Let $p_{I_{s,v}}(i_{s,v})$ be the probability that the first bit error in segment s occurs at bit position $i_{s,v}$ of partition v. Note that for the first bit error to occur at $i_{s,v}$, all the previous partitions of segment s have to be error free. Hence, $p_{I_{s,v}}(i_{s,v})$ is given as

$$p_{I_{s,v}}(i_{s,v}) = \prod_{t=1}^{v-1} \left(1-p^e_{s,t}\right)^{w_{s,t}} \left(1-p^e_{s,v}\right)^{i_{s,v}-1} p^e_{s,v}. \tag{4}$$

Now, by modifying the distortion model expressions presented in [37] and [38], the mean squared error in the image due to quantization and channel errors in partition v of segment s can be expressed as see (5), shown at the bottom of the page, where $MSE_{i_{s,v}}$ is the MSE due to the coefficients that are corrupted by the bit error. This MSE is different for the segments corresponding to the DC and AC layers, since the DC coefficients in the JPEG standard are DPCM coded, whereas the AC coefficients are not. For the DC layer, $MSE_{i_{s_v}}$ is given as see (6), shown at the bottom of the page, where a is a first-order auto-regressive process coefficient. The details of this derivation can be found in [37] and [38]. For the segments from AC layers, $MSE_{i_{s_v}}$ is given as

$$MSE_{i_{s,v}} = m_{s,v}\left(\sigma^2_{u,s} + \mu^2_{u,s}\right). \tag{7}$$

$$\begin{aligned} MSE_{s,v} = &\sum_{i_{s,v}=1}^{w_{s,v}} \left(\frac{M - m_{s,v} - \sum\limits_{t=1}^{v-1} M_{s,t}}{N} \left(\sigma^2_{\xi,s}+\mu^2_{\xi,s}\right) + MSE_{i_{s,v}} \right) p_{I_{s,v}}(i_{s,v}) \\ &+ \prod_{t=1}^{v-1} \left(1-p^e_{s,t}\right)^{w_{s,t}} \left(1-p^e_{s,v}\right)^{w_{s,v}} \left(\sigma^2_{\xi,s}+\mu^2_{\xi,s}\right) M_{s,v} \end{aligned} \tag{5}$$

$$MSE_{i_{s,v}} = \begin{cases} \frac{1}{N}\left[m_{s,v}\cdot\left(2\left(\sigma^2_{u,s}+\mu^2_s\right) + \left(\sigma^2_{\xi,s}+\mu^2_{\xi,s}\right)\right) - 2\sum\limits_{j=1}^{m_{s,v}} a^{|j|}\left(\sigma^2_{u,s}+\mu^2_{u,s}\right)\right], & m_{s,v} = 1\ldots M-1 \\ \frac{1}{N}\left[M\left(\sigma^2_{u,s}+\mu^2_{u,s}\right)\right], & m_{s,v} = M \end{cases} \tag{6}$$

Finally, $MSE_{k,n}(x_{k,n})$ can be expressed as a sum of the MSEs due to individual segments and partitions of segments

$$MSE_{k,n}(x_{k,n}) = \sum_{\mathbb{S}(k,n)} MSE_{\mathbb{S}(k,n)} \tag{8}$$

where $\mathbb{S}(k,n)$ is a set containing pairs of segment number s and partition number v contained in k^{th} stream of block number n. Note that the partitioning of segments into different blocks depends on the total number of bits in the image, and the block length.

The MSE expressions in (5) and (8) are expressed as a function of the instantaneous BER (in terms of $p^e_{s,v}$ for different segments and partitions in a block). Since the problem formulation is in terms of transmission power/energy, these equations need to be related to transmission power (or equivalently SNR). If the channel is known at the transmitter, these expressions can be easily derived for the MMSE receiver by modifying the signal to interference and noise ratio (SINR) for the equal power case [41]. Thus, for unequal power, the SINR $\eta_{k,n}$ for the k^{th} stream of the n^{th} block can be expressed as

$$\eta_{k,n} = \frac{1}{[(\rho_{k,k,n}\mathbf{H}^H\mathbf{H} + \mathbf{I}_4)^{-1}]_{k,k}} - 1 \tag{9}$$

where $\rho_{k,k,n}$ is the k^{th} column and k^{th} row entry of $\mathbf{X}_n$. This SINR can be easily related to the instantaneous BER for 4-QAM using the following expression [42]:

$$BER_{k,n} = \frac{1}{2}[1 - (1 - Q(\sqrt{\eta_{n,k}}))^2] \tag{10}$$

where $Q(\cdot)$ is the Q function. Using these relations between SINR, BER, $\mathbf{X}_n$ and $\mathbf{x}_n$, the MSE can be related to the transmission power (energy) x_n.

C. Solution to the Minimization Problem

Using expressions (4)–(10), unequal power allocation can be performed in real-time using well developed optimization techniques. Note that the optimization problem of (2) and (3) is not a convex problem, and, hence, the solution might not be global. Due to the complex nature of the expressions for MSE, it is mathematically intractable to derive a closed form solution to the power optimization problem. There are many well developed techniques to obtain numerical solutions to such optimization problems. Here, the Kuhn-Tucker equations along with a sequential quadratic programming (SQP) method are used to solve this constrained multivariable minimization problem. The SQP method formulates and solves a quadratic programming (QP) subproblem at each iteration of the optimization process. This method employs the Broyden-Fletcher-Goldfarb-Shanno (BFGS) formula to estimate the Hessian of the Lagrangian at each iteration. An active set strategy similar to that described in [43] is used to solve the QP subproblem. To solve this SQP problem, MATLAB's optimization toolbox is used. Using this method, the optimum MSE and the corresponding transmission power vector are obtained.

An interesting thing to note is that at any given instant, the channel from a particular transmit antenna to the receive antennas might be better than the channel corresponding to the remaining transmit antennas. In fact, the channels from different transmit antennas to the receive antennas are very likely to be different at different times. Therefore, a natural idea is to transmit more important streams from "more reliable" transmit antennas and less important streams from "less reliable" antennas. This makes sense intuitively since less power will be required by the most important stream if it is being transmitted from the best antenna as compared to that of a random antenna. Hence, more power can be allocated to less important streams resulting in further reduction of overall distortion. Since the channel stays constant for a block of symbols, and then changes, an antenna selection process needs to be performed for each block of symbols in real ime. Antenna selection is a research problem of its own and there is a large amount of literature available on this topic. Instead of using any of the sophisticated antenna selection methods that are available, a very simple method of antenna selection based on SINR is used to keep the optimization problem simple and computationally less intensive.

At any channel instantiation, first the four SINRs for the four streams are computed using (9) for the case of equal power allocation. Then, the transmit antenna corresponding to the stream with highest SINR is selected to transmit the most important stream, the transmit antenna with the second highest SINR to transmit the second most important stream and so on. This method of antenna selection is static as it assigns different antennas to different streams at the beginning of the optimization procedure for each channel instantiation based on the equal power case. Though this scheme will give us the best transmit antenna in terms of SINR, it might not give us the second best antenna and so on. This is because the SINR for the streams transmitted from different antennas changes when the transmit power is varied between antennas, which in turn can change the order of best to worse SINR streams, hence making another antenna the second best rather than the one found initially, in terms of SINR. A better scheme would be to assign transmit antennas dynamically during the optimization procedure, however, that will increase the computational complexity since more iterations would be needed. Nevertheless, as observed by simulations, this antenna selection scheme does give significantly better results than that of randomly assigning antennas to different streams. Antenna selection does not create any problem at the receiver since the receiver computes the received SINR for each stream and hence discovers the order of importance of the streams. After antenna selection, constrained power optimization is performed iteratively by searching through different combinations of transmission power allocation to different streams. MSE is computed for these different combinations of transmission power using (4)–(8), and the power allocation vector corresponding to minimum the MSE is chosen. The total transmit power at any given instant is kept constant.

Note that the main goal of the problem is to demonstrate that significant quality gains can be achieved by using unequal power allocation matched to image statistics in a MIMO system. Once the problem is formulated, well established optimization algorithms can be used to find the optimal solution. As discussed above, a SQP method is used to find the minimum MSE and the corresponding transmission power allocation scheme. However,

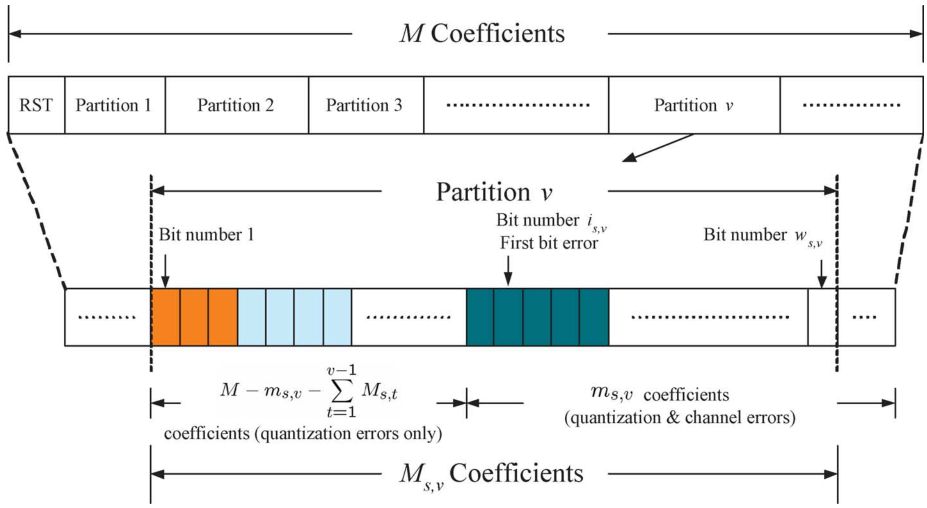

Fig. 2. Illustration of segment "*s*" and partition "*v*".

like most of the numerical optimization methods, this method is also computationally extensive. To reduce the number of computations performed, a very simple suboptimal power allocation method is proposed in the following subsection. The results for both of the methods are presented and compared in Section V.

D. *Suboptimal Power Allocation Algorithm*

Our original optimization problem is a minimization problem in four variables. Most numerical optimization methods are computationally intensive for optimization problems with more than two variables. For real-time applications, it is necessary that the power optimization procedure should be computationally nonintensive. The number of computations can be significantly reduced by devising simple suboptimal algorithms that divide the original problem into optimization problems with fewer numbers of variables, without imposing a large penalty on performance. Based on this idea, a suboptimal algorithm for the power allocation problem is developed in this section. This algorithm quantizes the transmit power for different streams and essentially breaks down the four variable optimization problem into an iterative two variable optimization problem.

After performing antenna selection as discussed in the previous section, the range of transmit power for each stream is quantized in M_k ($k = 1 \ldots 4$, $M_4 = M_3$) levels, where $k = 1$ corresponds to the most important and $k = 4$ to the least important stream. The algorithm starts by setting the initial minimum MSE ($MSE_{\min}$) to a very large value (infinity), the total available power to E_s and the total allocated power E_A to zero. The algorithm then varies the transmit power for the $1st$ stream in steps of $\Delta_1 = E_s/M_1$ from $E_s - E_s/M_1$ to E_s/M_1, while varying the transmit power (energy) for streams 2 to 4 equally in steps of $\Delta_1/3$. The main idea here is to vary the power for stream 1 through the range of available power in steps while dividing the remaining power equally between the remaining three layers. The algorithm computes MSE at each step, and if the MSE is lower than the previous $MSE_{\min}$, it updates $MSE_{\min}$ to this value. The computations for the $1st$ stream are stopped when either the entire range of available power has been spanned or when the SINR for the $1st$ stream becomes lower than the SINR for any of the other three streams. The minimum MSE of all these combinations is then assigned to $MSE_{\min}$ and the corresponding transmission power for stream 1 is fixed ($x_{1,n}$). The allocated power is modified to $E_A = E_A + x_{1,n}$ and the same process is repeated for the remaining streams. While finding the transmission power for the k^{th} stream, the transmission power for the $1st$ to $(k-1)^{th}$ streams are fixed (already found), the transmit power for the k^{th} stream is varied in steps of Δ_k, and the transmit powers for streams $k+1 \ldots 4$ are varied equally in steps of $\Delta_k/4 - k$. This way, at any given time the optimization problem is essentially a two variable constrained minimization problem, hence reducing the computational complexity significantly. This algorithm is summarized below.

Initialize: $k = 1$, $m = 1$, $E_A = 0$, $MSE_{\min} = \infty$,
$\Delta_1 = E_s/M_1$
Step 1: Do
$x_{k,n} = E_s - m\Delta_k - E_A$,
$x_{k+1,n} = \cdots = x_{4,n} = m\Delta_k/(4-k)$.
Find $MSE(\mathbf{x}_n)$.
If $MSE(\mathbf{x}_n) < MSE_{\min}$,
then $MSE_{\min} = MSE(\mathbf{x}_n)$, $x_{\min} = x_{k,n}$.
$m = m + 1$.
While $m < M_k$ AND $\eta_{k,n} \geq \eta_{k+1,n} \ldots \eta_{4,n}$
Step 2: $x_{k,n} = x_{\min}$, $E_A = E_A + x_{k,n}$,
$k = k + 1$, $m = 1$, $\Delta_k = (E_s - E_A)/M_k$
If $k < 4$ then goto Step 1,
else $MSE_{\min}$ has the minimum value of
MSE, and $\mathbf{x}_n$ has the corresponding transmit
power for different streams.

This algorithm uses the fact that the received SINR for a more important stream needs to be greater than the received SINR for a less important stream to minimize the distortion. Using this fact, this algorithm does not need not to compute the distortion at all the quantized power levels. Note that after finding the best suited power for a stream, this algorithm does not vary the power for that stream during iterations for the remaining streams.

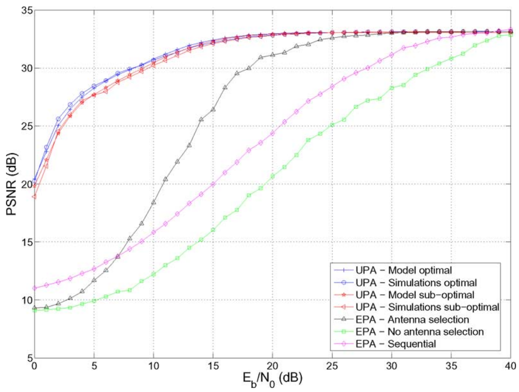

Fig. 3. PSNR curves for UPA and EPA methods for "Dog" image.

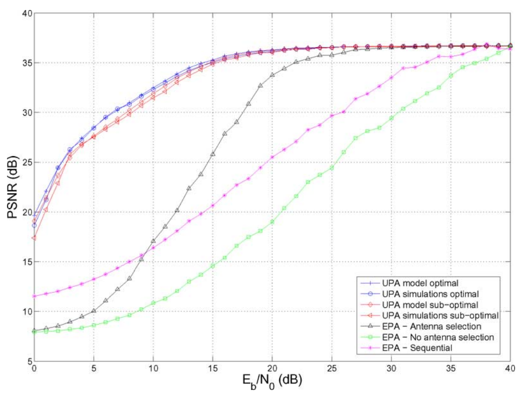

Fig. 4. PSNR curves for UPA and EPA methods for "Lena" image.

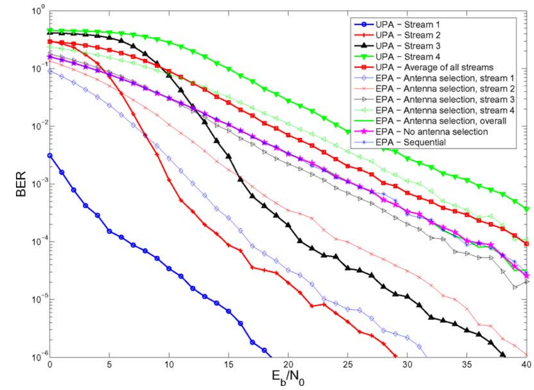

Fig. 5. BER curves for UPA and EPA methods for "Dog" image.

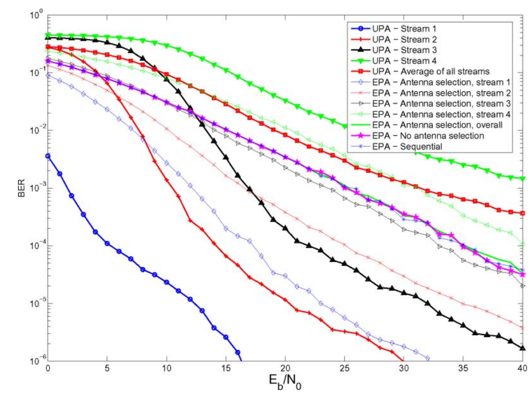

Fig. 6. BER curves for UPA and EPA methods for "Lena" image.

E. Note on the Convergence of These Methods

The power allocation optimization problem is not convex. Both the SQP and the suboptimal algorithms are not guaranteed to give a globally optimum point as their solution. The solution will depend on the starting point for the SQP optimization and the number of power level steps for each stream (quantization) for the suboptimal algorithm.

IV. Simulations Details

We used a database[1] of 50 grayscale 512×512 randomly selected natural grayscale images was used for the simulations. 1.25 bits per pixel source coding rate was used for all the images. We assumed that the channel was constant for 250 symbols, corresponding to 500 bits for 4-QAM modulation. Unequal power allocation was performed using the distortion model described in Section III-B to predict the MSE for MATLAB's (SQP) optimization as well as the suboptimal algorithm, and the resulting power allocation was used to transmit different streams simultaneously over different antennas. The model parameters, namely the unquantized coefficient mean and variance, the quantization error mean and variance, and the first order auto-regressive process parameter "a" for each segment were found using the original unquantized image and the quantization matrix. The values of $M_1 = 30$, $M_2 = 20$, $M_3 = M_4 = 10$ were numbers of quantized power levels that were used for different streams for the suboptimal power allocation method. The actual MSE at the receiver was also computed using the original unquantized image and the distorted image to compare how closely the model predicts the actual distortion obtained via simulations. MSE was converted to PSNR using the simple relation $\mathrm{PSNR} = 10\log_{10}(255^2/\mathrm{MSE})$, and PSNR versus average channel SNR curves were plotted. 500 channel instantiations were used at each SNR.

Figs. 3 and 4 show PSNR versus SNR curves for "Dog" and "Lena" images respectively for unequal power allocation using the optimization method of MATLAB (SQP) and the suboptimal algorithm. The distortion model in Section III-B was used to predict the MSE in real-time for these optimization procedures. The PSNR curves obtained via simulations when the image is transmitted using the power obtained using these optimization procedures are also shown. In these figures, the curves labeled "optimal" are those obtained using the SQP optimization. For comparison, the PSNR curves for three different equal power allocation methods are also shown. In one of these methods, antenna selection was performed, and more important streams were transmitted using better antennas. This scheme is labeled as "EPA—Antenna selection". In the scheme labeled "EPA—No antenna selection" in Fig. 3, no antenna selection was performed and streams were transmitted from fixed preallocated antennas. The same progressive JPEG coder was used for these two schemes as for the unequal power case. In the third scheme labeled "EPA—Sequential", a sequential (also called baseline) JPEG coder was used so that the subbands are

[1]These images were randomly selected from the two-CD set of "Austin & Vicinity—The world of nature" and "Austin and Vicinity—The human world".

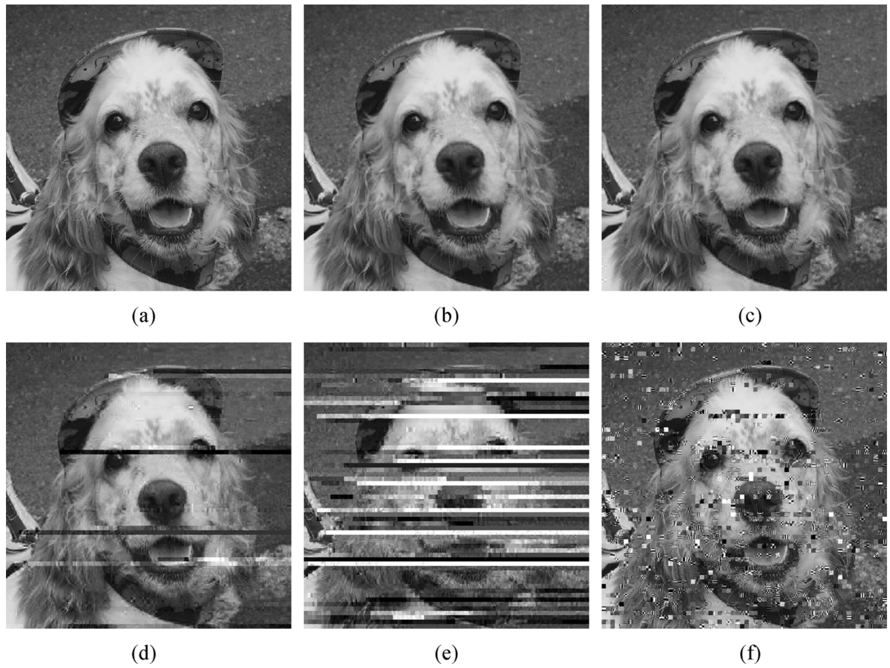

Fig. 7. Dog image results for different power allocation schemes at 10-dB SNR. (a) Original unquantized image. (b) UPA, optimal allocation. (c) UPA, suboptimal method. (d) EPA with antenna selection. (e) EPA (no antenna selection). (f) EPA with sequential JPEG.

distributed uniformly in all the streams and a fair comparison is observed. An equal number of *RST* markers and the same source coding rate was used as in progressive JPEG. Figs. 5 and 6 show the BER curves for "Dog" and "Lena" images, respectively, for different streams using suboptimal UPA and EPA methods. For the UPA and "EPA—Antenna selection" cases, the BERs for individual streams are shown along with the average BER of all four streams. Since the BER for equal power allocation cases (both sequential and progressive) is the same for all the streams, only the total BER is shown. Tables I and II compare the PSNR results for different power allocation methods at various SNRs for the "Dog" and "Lena" images. Results for the UPA and EPA schemes for the "Dog" image at 10-dB SNR and the "Lena" image at 5 dB SNR are shown in Figs. 7 and 8, respectively.

V. Results and Discussion

It is evident from the PSNR curves in Figs. 3 and 4 that the proposed unequal power allocation scheme performs significantly better than allocating power equally to different streams. At 5 dB SNR, the PSNR gain for the UPA scheme has an advantage of approximately 14 dB over sequential JPEG with equal power allocation for both the images. Also, the suboptimal power allocation method performs very close to the optimal power allocation scheme. The difference in PSNR between the SQP method (MATLAB's numerical solution) and the suboptimal algorithm is within 1.5 dB at all points. The suboptimal method performs close to the optimal method because the suboptimal method spans through the whole range of available power for the most important stream (or while SINR for the most important stream is greater than the SINRs for less important streams) before fixing it to the power level that causes minimum distortion. It then spans through the whole range of leftover power to allocate power to the next important streams and so on. Hence, this method has a high chance of performing close to the optimal method as long as number of steps in power levels for each stream are high enough (low quantization). In terms of computational complexity, on the average for each block, the optimal power allocation scheme took 350 MSE evaluations to converge to a solution, whereas the suboptimal method evaluated MSE 26 times on average, reducing the computational complexity better than an order of magnitude. Furthermore, to confirm that the solution is not a local minima, MATLAB's optimization was carried out multiple times with different starting points. This further increased its computational complexity as compared to the suboptimal algorithm.

Another encouraging thing to note is that the amount of distortion predicted by the distortion model during the optimization procedure is very close (within 1 dB) to that of the actual amount obtained via transmission simulations. The difference in PSNR obtained using the model and the simulations is mainly because the model predicts the average MSE in the image due to bit errors in the entropy coded image. The error detection by software decoder is not always 100% correct [38]. Due to this reason, we see this small difference in PSNR between the curves labeled Model Optimal (Model Suboptimal) and Simulations Optimal (Simulations Suboptimal).

Figs. 5 and 6 show the BER curves for the UPA and EPA schemes. As can be seen from these figures, the BER for stream 1 (the most important stream) for unequal power allocation was much lower than all the other streams for unequal and equal power allocation. Also, the BER for stream 4 (the least important stream) for UPA was the worse of all the streams. The average BER of all the 4 streams for UPA is also higher than the average BER for equal power allocation schemes. Although the

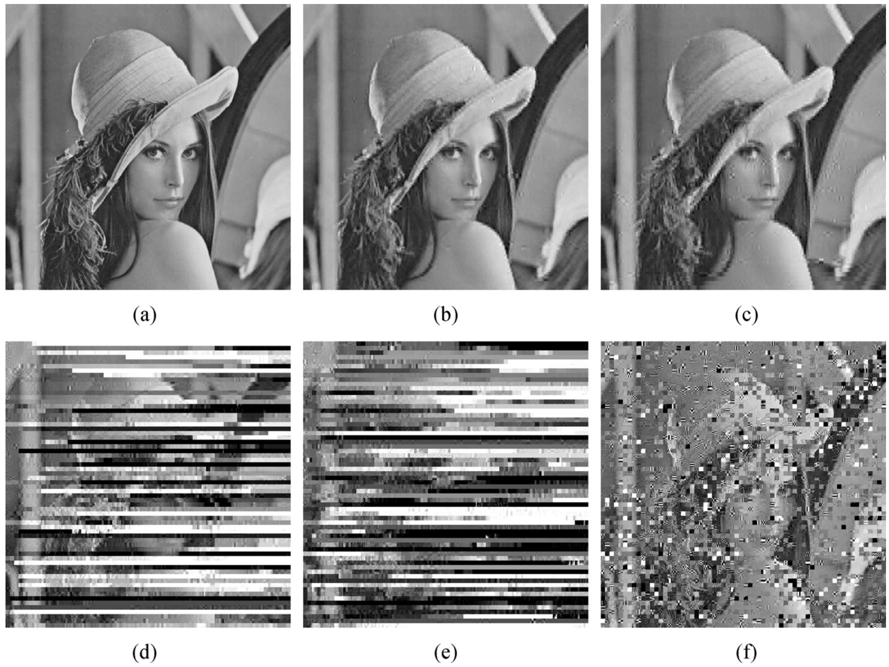

Fig. 8. Lena image results for different power allocation schemes at 5-dB SNR. (a) Original unquantized image. (b) UPA, optimal allocation. (c) UPA, suboptimal method. (d) EPA with antenna selection. (e) EPA (no antenna selection). (f) EPA with sequential JPEG.

TABLE I
PSNR VALUES IN DB FOR DIFFERENT POWER ALLOCATION SCHEMES FOR "DOG" IMAGE

SNR (dB)	0	5	10	15	20	30	40
UPA - Optimal	20.25	28.47	30.67	32.20	32.84	33.13	33.16
UPA - Sub-optimal	18.91	27.67	30.22	32.11	32.83	33.13	33.16
EPA - Antenna Selection	9.31	11.69	18.4	26.41	31.12	33.02	33.16
EPA - No Antenna Selection	9.11	9.93	12.22	16.03	20.67	28.3	32.88
EPA - Sequential	11.02	12.68	15.84	19.98	24.38	31.14	33.34

average BER was higher for UPA, significantly better performance in terms of quality (PSNR) was obtained for UPA. This is because it is the stream with the highest contribution toward image quality, and, hence, it is this stream that requires maximum transmission power and reliability. This shows that with a constraint on total transmission power at any instant, significant quality gains can still be achieved by allocating more power to more important streams at the cost of reduced power for less important streams.

Different streams for the EPA scheme with antenna selection also have different BERs. The average BER of all these streams is approximately the same, however, as that of the EPA scheme without antenna selection, and sequential JPEG with EPA. Also note that EPA with antenna selection performs better in terms of PSNR as compared to EPA without antenna selection (for progressive JPEG) at all points, and better than EPA for sequential JPEG for medium to high SNR range. This shows that the idea of antenna selection provides better performance than randomly assigning transmit antennas to different streams. The quality gain for UPA is also obvious from the images shown in Figs. 7 and 8.

Similar performance gains were obtained for all the other images as well. These results are very encouraging because they show that significant quality gains can be achieved by using image statistics for power allocation in MIMO systems. Although the power allocation method proposed in this paper only uses four transmit and four receive antennas, this approach can be extended easily to any number of transmit and receive antennas with slight modifications.

There can be many real-world applications of our proposed UPA method. A feasible application can be to capture and transmit images in a MIMO cellular environment. Another application can be wireless security cameras transmitting images at regular intervals with a much better image quality. In both these cases, high quality images can be transmitted with an overall transmit power constraint. This method can also be extended to power constrained efficient video transmission over MIMO systems using our distortion model for video [44].

VI. CONCLUSION

In this paper, we presented an unequal power allocation scheme for the transmission of JPEG compressed images over MIMO systems employing spatial multiplexing. The image was divided into 4 different streams with unequal contribution to total image quality. These different streams were transmitted using different antennas with unequal power with the goal of minimizing the distortion in the transmitted image. The overall transmit power is kept constant at any given instant.

TABLE II
PSNR VALUES IN DB FOR DIFFERENT POWER ALLOCATION SCHEMES FOR "LENA" IMAGE

SNR (dB)	0	5	10	15	20	30	40
UPA - Optimal	18.65	28.43	32.28	35.03	36.12	36.66	36.72
UPA - Sub-optimal	17.39	27.53	31.46	34.85	36.03	36.65	36.72
EPA - Antenna Selection	8.06	10.04	17.05	25.80	33.74	36.52	36.72
EPA - No Antenna Selection	7.93	8.60	10.83	14.58	19.01	29.43	36.63
EPA - Sequential	11.53	13.24	16.40	20.65	25.49	33.48	36.37

We also presented a suboptimal power allocation algorithm as a numerical solution to the unequal power allocation problem. Results show that our unequal power allocation scheme provides significant gains in terms of PSNR over various equal power allocation schemes. This gain is as high as 14 dB at low SNRs. Furthermore, our suboptimal algorithm performs very close to optimal power allocation. These results indicate that significant quality gains can be achieved if the source statistics are taken into account while designing transmission schemes without imposing any penalty on resources. To the best of our knowledge no unequal power allocation scheme exists for image transmission over MIMO systems. We plan to extend this work to different video coding schemes and advanced space-time coding techniques.

REFERENCES

[1] Y. Wang, S. Wenger, J. Wen, and A. Katsaggelos, "Error resilient video coding techniques," *IEEE Signal Process. Mag.*, vol. 17, no. 4, pp. 61–82, Apr. 2000.

[2] A. J. Goldsmith and M. Effros, "Joint design of fixed-rate source codes and multiresolution channel codes," *IEEE Trans. Commun.*, vol. 46, no. 10, pp. 1301–1312, Oct. 1998.

[3] N. Farvardin and V. Vaishampayan, "Optimal quantizer design for noisy channels: An approach to combined source-channel coding," *IEEE Trans. Inf. Theory*, vol. IT-33, no. 11, pp. 827–838, Nov. 1987.

[4] P. Sherwood and K. Zeger, "Error protection for progressive image transmission over memoryless and fading channels," *IEEE Trans. Commun.*, vol. 46, no. 12, pp. 1555–1559, Dec. 1998.

[5] J. W. Modestino and D. G. Daut, "Combined source-channel coding of images," *IEEE Trans. Commun.*, vol. COM-27, no. 11, pp. 1644–1659, Nov. 1979.

[6] J. W. Modestino, D. G. Daut, and A. L. Vickers, "Combined source-channel coding of images using the block cosine transmform," *IEEE Trans. Commun.*, vol. COM-29, pp. 1261–1274, Sep. 1981.

[7] V. Chande and N. Farvardin, "Progressive transmission of images over memoryless noisy channels," *IEEE J. Sel. Areas Commun.*, vol. 18, no. 6, pp. 850–860, Jun. 2000.

[8] P. G. Sherwood and K. Zeger, "Progressive image coding for noisy channels," *IEEE Signal Process. Lett.*, vol. 4, no. 7, pp. 189–191, Jul. 1997.

[9] Y. Eisenberg, C. Luna, T. Pappas, R. Berry, and A. Katsaggelos, "Joint source coding and transmission power management for energy efficient wireless video communications," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 12, no. 6, pp. 411–424, Jun. 2002.

[10] L. Atzori, "Transmission of JPEG2000 images over wireless channels with unequal power distribution," *IEEE Trans. Consum. Electron.*, vol. 49, no. 11, pp. 883–888, Nov. 2003.

[11] I. Kozintsev and K. Ramchandran, "Robust image transmission over energy-constrained time-varying channels using multiresolution joint source-channel coding," *IEEE Trans. Signal Process.*, vol. 46, no. 4, pp. 1012–26, Apr. 1998.

[12] Q. Zhang, Z. Ji, W. Zhu, and Y.-Q. Zhang, "Power-minimized bit allocation for video communication over wireless channels," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 12, no. 6, pp. 398–410, Jun. 2002.

[13] H. Yousefi'zadeh, H. Jafarkhani, and M. Moshfeghi, "Power optimization of wireless media systems with space-time block codes," *IEEE Trans. Image Process.*, vol. 13, no. 7, pp. 873–884, Jul. 2004.

[14] X. Lu, Y. Wang, and E. Erkip, "Power efficient h.263 video transmission over wireless channels," in *Proc. IEEE Int. Conf. Image Processing*, 2002, vol. 1, pp. I–533–I–536.

[15] I.-M. Kim and H.-M. Kim, "An optimum power management scheme for wireless video service in cdma systems," *IEEE Trans. Wireless Commun.*, vol. 2, no. 1, pp. 81–91, Jan. 2003.

[16] X. Tian, "Efficient transmission power allocation for wireless video communications," in *Proc. IEEE Wireless Communications and Networking Conf.*, 2004, vol. 4, pp. 2058–2063.

[17] Z. Ji, Q. Zhang, W. Zhu, Z. Guo, and J. Lu, "Power-efficient mpeg-4 fgs video transmission over mimo-ofdm systems," in *Proc. IEEE Int. Conf. Communications*, 2003, vol. 5, pp. 3398–3402.

[18] C. Luna, Y. Eisenberg, R. Berry, T. Pappas, and A. Katsaggelos, "Joint source coding and data rate adaptation for energy efficient wireless video streaming," *IEEE J. Sel. Areas Commun.*, vol. 21, no. 10, pp. 1710–1720, Oct. 2003.

[19] W. Yu, Z. Sahinoglu, and A. Vetro, "Energy efficient jpeg 2000 image transmission over wireless sensor networks," in *Proc. IEEE Global Telecommunications Conf.*, 2004, vol. 5, pp. 2738–2743.

[20] S. Appadwedula, D. Jones, K. Ramchandran, and L. Qian, "Joint source channel matching for a wireless image transmission," in *Proc. IEEE Int. Conf. Image Processing*, 1998, vol. 2, pp. 137–141.

[21] M. J. Ruf and J. W. Modestino, "Operational rate-distortion performance for joint source and channel coding of images," *IEEE Trans. Image Process.*, vol. 8, no. 3, pp. 305–320, Mar. 1999.

[22] A. A. Alatan, M. Zhao, and A. N. Akansu, "Unequal error protection of SPIHT encoded image bit streams," *IEEE J. Sel. Areas Commun.*, vol. 18, no. 6, pp. 814–818, Jun. 2000.

[23] V. Stankovic, R. Hamzaoui, and Z. Xiong, "Efficient channel code rate selection algorithms for forward error correction of packetized multimedia bitstreams in varying channels," *IEEE Trans. Multimedia*, vol. 6, no. 2, pp. 240–248, Feb. 2004.

[24] S. Dumitrescu, X. Wu, and Z. Wang, "Globally optimal uneven error-protected packetization of scalable code streams," *IEEE Trans. Multimedia*, vol. 6, no. 2, pp. 230–239, Feb., 2004.

[25] P. Cosman, J. Rogers, P. Sherwood, and K. Zeger, "Combined forward error control and packetized zerotree wavelet encoding for transmission of images over varying channels," *IEEE Trans. Image Process.*, vol. 9, no. 6, pp. 982–993, Jun. 1998.

[26] H. Zheng and K. Liu, "The subband modulation: A joint power and rate allocation frameworkfor subband image and video transmission," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 9, no. 5, pp. 823–838, May 1999.

[27] Q. Zhang, W. Zhu, Z. Ji, and Y.-Q. Zhang, "A power-optimized joint source channel coding for scalable videostreaming over wireless channel," in *Proc. IEEE Int. Symp. Circuits and Systems*, 2001, vol. 5, pp. 137–140.

[28] Z. Ji, Q. Zhang, W. Zhu, and Y.-Q. Zhang, "End-to-end power-optimized video communication over wirelesschannels," in *Proc. IEEE 4th Workshop Multimedia Signal Processing*, 2001, pp. 447–452.

[29] H. Jafarkhani, H. Yousefi'zadeh, and M. Moshfeghi, "Power optimization of memoryless wireless media systems with space-time block codes," in *Proc. Global Telecommunications Conf.*, 2003, vol. 1, pp. 123–127.

[30] I.-M. Kim and H.-M. Kim, "Transmit power optimization for video transmission over slowly-varying rayleigh-fading channels in cdma systems," *IEEE Trans. Wireless Communications*, vol. 3, no. 5, pp. 1411–1415, May, 2004.

[31] Y. S. Chan and J. Modestino, "Transport of scalable video over cdma wireless networks: a jointsource coding and power control approach," in *Proc. IEEE Inf. Conf. Image Processing*, 2001, vol. 2, pp. 973–976.

[32] S. M. Alamouti, "A simple transmit diversity technique for wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 16, no. 10, pp. 1451–1458, Oct. 1998.

[33] G. J. Foschini, "Layered space-time architecture for wireless communication in a fading environment when using multiple antennas," *Bell Labs Tech. J.*, vol. 1, no. 2, pp. 41–59, 1996.

[34] V. Tarokh, N. Seshadri, and A. R. Calderbank, "Space-time codes for high data rate wireless communication: Performance criterion and code construction," *IEEE Trans. Inf. Theory*, vol. 44, no. 3, pp. 744–765, Mar. 1998.

[35] V. Tarokh, H. Jafarkhani, and A. R. Calderbank, "Space-time block codes from orthogonal designs," *IEEE Trans. Inf. Theory*, no. 7, pp. 1456–1467, Jul. 1999.

[36] W. B. Pennebaker and J. L. Mitchell, *JPEG Still Image Data Compression Standard*. New York: Van Nostrand Reinhold, 1993.

[37] M. F. Sabir, H. R. Sheikh, R. W. Heath, Jr., and A. C. Bovik, "A joint source-channel distortion model for JPEG comrpessed images," in *Proc. IEEE Int. Conf. Image Processing*, 2004, pp. 3249–3252.

[38] M. F. Sabir, H. R. Sheikh, R. W. Heath, Jr., and A. C. Bovik, "A joint source-channel distortion model for JPEG comrpessed images," *IEEE Trans. Image Process.*, vol. 15, pp. 1349–1364, 2006.

[39] C. Cozzo and B. Hughes, "Joint channel estimation and data detection in space-time communications," *IEEE Trans. Communications*, vol. 51, no. 8, pp. 1266–1270, Aug. 2003.

[40] R. Trepkowski, "Channel Estimation Strategies for Coded MIMO Systems," M.S. thesis, Virginia Polytechnic Institute and State University, Blacksburg, 2004.

[41] A. Paulraj, R. Nabar, and D. Gore, *Introduction to Space-Time Wireless Communications*. Cambridge, U.K.: Cambridge Univ. Press, 2003.

[42] M. K. Simon and M. S. Alouni, *Digital Communication Over Fading Channels*. New York: Wiley, 2000.

[43] P. E. Gill, W. Murray, and M. H. Wright, *Practical Optimization*. London, U.K.: Academic, 1981.

[44] M. F. Sabir, R. W. Heath, Jr., and A. C. Bovik, "Joint source-channel distortion modeling for MPEG-4 video," *IEEE Trans. Image Process.*, vol. 18, no. 1, pp. 90–105, Jan. 2009.

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