Optimal Bit Allocation for Channel-Adaptive Multiple Description Coding *

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ABSTRACT

Multiple Description Coding (MDC) techniques have been explored in recent years as an alternative to other methods to provide robustness to multimedia information in the presence of losses. In a MDC approach some redundancy is preserved in the source coding so that, after appropriate packetization, if packet losses occur it is possible to recover by exploiting the redundancy (statistical or deterministic) between what was received and what was lost. While MDC techniques have shown some promising results, one potential drawback is the fact that changing their redundancy level may entail significant changes to the system. Since the level of redundancy should be adjusted to match the specific channel conditions, the difficulty in adapting can be a significant problem for time varying transmission scenarios. As an example, MDC techniques based on transform coding would require a modification of the transform at encoder and decoder each time the channel conditions change. In our previous work, we have proposed a simple approach for MDC that involves using a polyphase transform and deterministic redundancy (e.g., each sample of input data is transmitted several times, with different coding rates). This approach is useful in that it greatly simplifies the design of a MDC scheme, since the rate allocation determines the amount of redundancy. Moreover, it provides a great deal of flexibility as it enables the choice of redundancy to be almost arbitrary. To demonstrate the effectiveness of our system we introduce an optimal bit allocation algorithm that allows us to select the amount of redundancy to be introduced in the signal that best matches a given target packet loss rate. It is clear that such a trade-off exists, as the level of redundancy should increase when the packet loss rate increases, at the cost of some degradation in the corresponding error free performance. Our results show significant differences between optimal and suboptimal choices of redundancy. Moreover, given that the decoder remains unchanged when the bit allocation changes it is possible to adapt very simply to the changes in channel behavior without requiring a change in the packet sizes, or the structure of the decoder.

Keywords: Bit allocation, Multiple description coding, Adaptive channel error protection

1. INTRODUCTION

One of the major challenges in achieving widespread delivery of real-time multimedia information comes in enabling such delivery over channels that are either subject to losses or suffer from variable delay. In this paper we concentrate on transmission environments, such as the Internet, where packet losses occur. These losses occur because packets are dropped as network queues fill up, or because network congestion delays their arrival to the receiver so that they cannot be decoded before their scheduled playback time. A majority of research dealing with lossy transmission environments has focused its attention on Forward Error Correction (FEC)[1] and Automatic Repeat Request (ARQ)[2] schemes, which correct errors at the destination and request retransmission, respectively. However, ARQ may not be a practical solution if transmission is delay-constrained, especially when round-trip times (RTTs) are long, or when the environment does not support feedback to begin with. On the other hand, although FEC (which operates by adding redundancy to the original data) has been used to recover from bit errors, it would require a significant amount of interleaving in order to be used in a environment subject to packet losses. Moreover, FEC is most effective when

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applied in an Unequal Error Protection (UEP) mode, i.e., such that we can determine which parts of the multimedia stream require more protection.

Given the added complexity of employing UEP codes, and the difficulty in designing systems where sufficiently fine granularity in error protection is possible, introducing redundancy in the source bitstream may be an attractive alternative. As an approach for source domain redundancy, multiple description coding (MDC)[3] has been proposed as an effective way to provide robustness with graceful degradation under packet losses. MDC is particularly useful in scenarios where channels with unequal error protection are not available and retransmission is not desirable, as well as when there are strict delay constraints. Transmission of real-time media over the current Internet infrastructure seems to be particularly well suited for MDC techniques since (i) differentiated quality of service transmission has not been widely deployed, and (ii) RTTs can be significantly long.

In a MDC system the input signal is split into blocks and each block is represented by several descriptions. Then, these multiple descriptions of the source are sent to the receiver and it is assumed that random losses can affect each of the descriptions. Recovery of a particular block of data is possible as long as one of the packets carrying data of this block is received correctly. Unlike layered coding systems where layers are given different levels of importance, since enhancement layers are useless without the base layer, in a MDC system all descriptions are equally important, so that each of the descriptions of the source can be decoded independently. When more than one description is received the overall quality can be improved with respect to having a single description.

The recent interest on MDC has led to a flurry of proposed approaches. Most coding techniques proposed to date are optimized to generate two descriptions. Early examples include the Multiple Description Scalar Quantizer (MDSQ),[4] and more recent ones include Multiple Description Transform Coding (MDTC).[5,6] In a MDC system the basic trade-off arises in the selection of the amount of redundancy. As can be expected, if high redundancy is chosen, the performance under severe error conditions will be good, while the performance in an error free environment will be significantly worse than that of a non-redundant coder at the same rate. Moreover, the "right" level of redundancy may depend heavily on the specific target channel conditions, and therefore it would be useful to design MDC systems that can adapt to changing network conditions by adjusting their level of redundancy.

Several of the approaches mentioned above[4–6] involve the design of specific transforms or quantizers that have to be matched to the desired level of protection. In these schemes, adapting to changing network conditions would entail having encoder and decoder both change the transform and/or quantizers they use. These approaches are thus limited in their ability to adapt to changing transmission conditions.

As an alternative, in this paper we concentrate on a class of MDC approaches first introduced by Jiang et al[7] for image coding and extended by Miguel et al.[8] These approaches are related to earlier work on audio coding.[9] In these techniques, explicit redundancy is introduced, so that each sample in the input (for example each wavelet coefficient) is transmitted more than once and coded with different accuracy each time. This strategy has the drawback of leading to transmission of more samples than initially present in the source, and thus to inefficiency in cases of error-free transmission. However, this drawback is compensated by the extreme simplicity of the design, which relies on existing quantizers. As an example, wavelet based techniques[7,8] can use the well-known SPIHT coder[10] to encode the various sets of redundant information to achieve excellent performance while providing robustness.

In this paper we demonstrate how these explicit redundancy techniques have the additional advantage of providing very simple mechanisms for adaptation to changing network conditions. The key observation is that the level of redundancy can be selected by determining the number of times a given sample (or wavelet coefficient) is transmitted, and how many bits should be used for each of the redundant representations. In this paper we show how a *bit allocation* problem can be defined, where the goal is to choose the best distribution of redundancy for a given packet loss rate. We provide techniques to solve this problem and show how indeed different loss rates require different levels of redundancy. Note that by using bit allocation to determine the level of redundancy, not only the encoder can adjust itself in a simple manner, but in addition the decoder can handle packets with different levels of redundancy without requiring any significant changes to its structure (e.g. the same transform, entropy coding, etc will be used).

More specifically, the MDC technique used in this paper generates the various descriptions through a polyphase transform. Consider for example the case of a scalar source. This polyphase-based MDC will divide this source into even and odd samples (or more sets if more than two descriptions are transmitted), and will compress each sample using two different quantization scales (coarse and fine). Then this approach will transmit groups of samples where

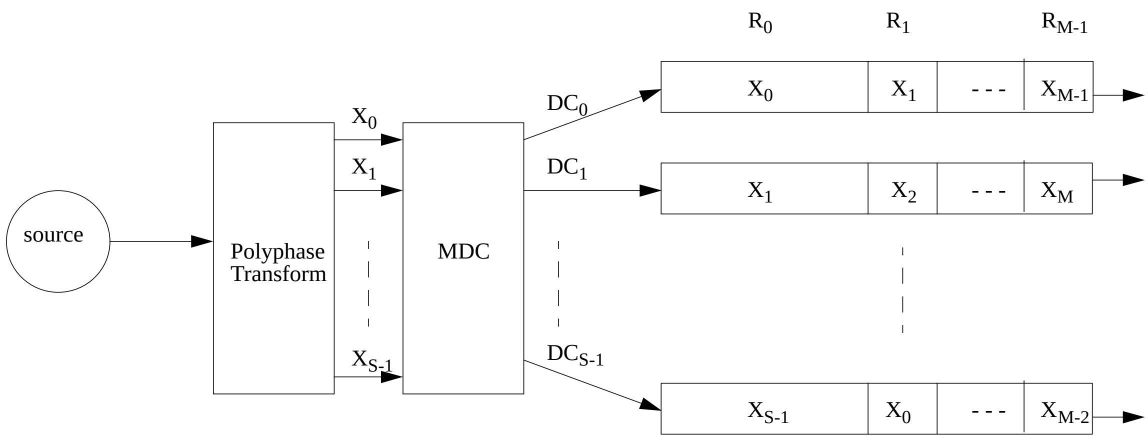


Figure 1. MDC system block diagram: S descriptions are generated by obtaining S polyphase components from the original signal. For each polyphase component M copies are transmitted. Each description carries the primary copy of one polyphase component, e.g., X_0 in DC_0, as well as redundant copies of some of the other polyphase components.

a set of coarsely quantized odd samples is combined with a set of finely quantized even samples (and vice versa, i.e. fine odd with coarse even.) Figure 1 provides an example for this approach in the case when S descriptions (DC_j for $j = 0, \ldots, S-1$) are used, based on polyphase components. In this case, each description contains M polyphase components from fine to coarse, each corresponding to different input samples. We will call each packet as described here a *description*, while we will call each redundant version of a polyphase component a *copy*. Each copy will be coded with a different quantizer. For example, in Figure 1 we show how M copies of each polyphase component are sent in each description, with rates ranging from R_0 to R_{M-1}. A given description contains the primary copy of one polyphase component, i.e., the copy coded at highest quality, along with lower resolution copies of other polyphase components. Note that our definition of description is consistent with the traditional one in MDC, i.e., the more descriptions are received the better the quality of the decoded signal.

The decoder operates by gathering the available information for each sample and then selecting for each polyphase component its highest quality copy to be used in the decoding; the remaining copies are discarded. For example, referring again to Figure 1, if DC_0 and DC_1 are both lost then all polyphase components X_2 through X_{S-1} will be decoded at their highest quality (R_0 bits), while X_0 and X_1 will be decoded with their highest received qualities (R_1 and R_2 bits, respectively).

Obviously, as the packet losses increases, the chances that the high quality copy of a given sample reaches the receiver diminish. In that situation, it would be better to distribute bits more evenly among all the copies of one sample. Therefore, the bit allocation we address in this paper is as follows. Given a known packet loss rate, our goal is to determine the optimal selection of the number of copies of a sample, as well as the amount of bits to assign to each copy. Thus, our goal is to determine the number of polyphase components to be included in a description, M, as well as the number of bits to be used for each polyphase component in a description, R_0, R_1, $\ldots$, R_{M-1}, such that the overall expected distortion at the receiver due to both coding and description loss is minimized for a given target channel, and for a given fixed rate budget.

It is worth noting that, unlike other recent MDC approaches, this polyphase-based MDC system can easily incorporate more than 2 descriptions. As will be seen this is required to provide robustness in high packet loss environments. An example of the polyphase transform from an original image of size 4×4 is provided to illustrate the definition in Figure 2.

This paper is organized as follows. In Section 2 we formalize the problem. An algorithm using Lagrangian optimization is introduced in Section 3. In Section 4, experimental results are provided as demonstration of the validity of our analyses. Finally, conclusion of this work and possible future work are discussed in Section 5.

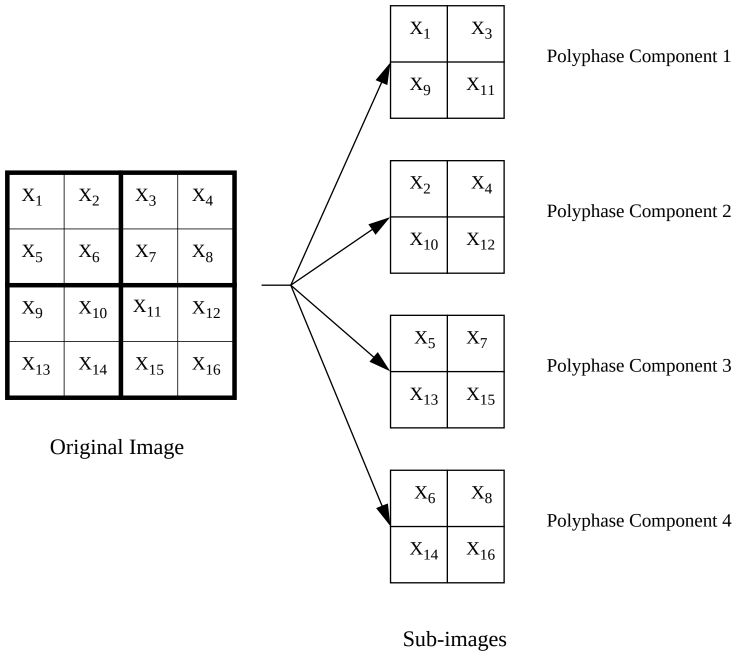


Figure 2. An example of polyphase transform when an original image, which is assumed to have a size of 4×4, is segmented into 4 blocks of size 2×2 where X_i represents the i^{th} pixel, $i = 1, \ldots, 16$, from an original image of total 16 pixels. The image pixels can be grouped according to the same spatial location in each block into each polyphase component and then finally four polyphase components is generated.

2. PROBLEM FORMULATION

As outlined in the introduction, our goal is to determine what the right amount of redundancy is for a given packet loss. Given that S polyphase components are generated and S packets are transmitted for each basic coding unit, our goal is to determine the number, M, of copies of each polyphase components to be transmitted. Obviously, if $M = 1$ we introduce no redundancy, and thus any packet loss will result in a polyphase component being lost. Conversely if $M = S$ the maximum redundancy is introduced, and therefore we will be able to reconstruct all the polyphase components of the input, albeit with different levels of quality, as long as at least one packet out of S is received. A related issue is that of determining, once M has been chosen, the number of bits to be assigned to each copy, i.e., R_0, R_1, ..., R_{M-1}. We will show how these two decisions can be made jointly in the process of performing a bit allocation, by reducing M to $M-k$ if R_{M-k}, ..., R_{M-1} are assigned a negative (or zero) number of bits in the bit allocation.

Clearly, the "right" choice for M will depend on the channel conditions, so that high redundancy is to be expected when packet losses are high and low redundancy should be used under low packet loss conditions. Since increasing the number of polyphase components in a description lowers the coding efficiency, but increases the robustness to errors, it is to be expected that at each loss rate an optimal redundancy can be determined. The goal in our bit allocation problem is to minimize the *expected distortion* at the receiver, after taking into account the effect of packet losses.

We start by evaluating the expected distortion at the receiver as a function of the packet loss rate. Assume a total bit rate budget R has been fixed, and assume a known probability that a description is considered lost, P, which is independent of the level of redundancy in each description (we assume that the packet size is fixed in all the scenarios we compare.) Given our total number of polyphase components, S, which is equal to the number of descriptions, and given the total number of samples N, if we transmit M polyphase components copies per description (one copy as primary data and the remaining $M-1$ copies as redundant data for polyphase components whose primary data is transmitted in another description), each polyphase component provides information for $\frac{N}{S}$ samples, and given a bit budget of R bits per sample on average, we have that the description size becomes $\frac{RN}{S}$ bits, which does not depend on the number of polyphase components in a description.

The primary copy is coded with rate R_0 while the other copies are coded with rates $R_1, \ldots, R_{M-1}$ with $R_m \geq R_n$ for $m < n$ and $m, n = 0, \ldots, M-1$. It is worth noting that our analysis in this work is description-based, i.e., we assume that each description is contained in a single packet. However similar analyses can be extended to a more practical packet-based framework, where the packet size is smaller than the size of a description. For instance, if we need to operate with small packet sizes, instead of considering the whole original image as the input in our analysis, we can divide the image into smaller blocks, and then extract the polyphase components in each of these blocks.

In order to estimate the distortion at the receiver we need to specify the decoding algorithm. In general, the decoder will receive more than one copy of each polyphase component. Then, the decoder will select among all those copies the one with the highest resolution (i.e., higher rate R_i) and will use it for reconstruction, while discarding all other copies. In the worst case, when no copy of a polyphase component has been received, the decoder will use the mean value of this polyphase component, which is assumed to be a known parameter available at receiver (e.g., this can be done by adding this information into a header of each outgoing packet), for reconstruction.

The expected distortion, $E[D]$, which we seek to minimize, statistically measures the reconstructed quality at the receiver. Given our proposed MDC approach, the distortion incurred for a given sample will be that corresponding to the highest quality copy received for that sample. In the worst case, if all copies are lost the distortion will be the variance of the source.

The expected distortion can be derived by determining the probabilities that the best copy for a given polyphase component is the one with index k. Note that we assume that the packet structures are identical and therefore it follows that these probabilities will be the same for each polyphase component. Denote P_k, $k = 0, \ldots, M$, the probability that copy k is the highest quality one received for the polyphase component under consideration. P_M is the probability that none of the copies is received (since there are only M copies, with indices 0 to $M-1$.) P_0 is the probability that the primary copy (with high rate equal to R_0) is received.

Since all the polyphase components are coded independently they can also be decoded independently of the other polyphase components. Let $D_j(R_k)$ be the distortion associated with copy k of the j-th polyphase component (coded with R_k bits.) Then the expected distortion for the j-th description will be

$$\sum_{k=0}^{k=M} P_k D_j(R_k).$$

Let us compute the probabilities. Consider the best scenario where, for instance, the description containing the j^{th} polyphase component as a primary data (i.e., it is coded with the highest bit rate R_0) is received. The probability of this case is equal to a summation of the probabilities of scenarios scenarios where copy 0 of the j^{th} polyphase component is received,

$$P_0 = \begin{pmatrix} S-1 \\ 0 \end{pmatrix} P^{S-1}(1-P) + \begin{pmatrix} S-1 \\ 1 \end{pmatrix} P^{S-2}(1-P)^2 \ldots + \begin{pmatrix} S-1 \\ S-1 \end{pmatrix} (1-P)^S = 1-P, \quad (1)$$

that is, we must ensure that the one packet carrying that copy arrives, independently of whether the others are received.

In general, the probability of receiving copy k as the one with highest quality for polyphase component j will be the probability of receiving the corresponding packet correctly, but losing the higher quality k copies, i.e. those coded at rates R_0 through R_{k-1}. This probability is with rate R_k is

$$P_k = \begin{pmatrix} S-(k+1) \\ 0 \end{pmatrix} P^{S-1}(1-P) + \begin{pmatrix} S-(k+1) \\ 1 \end{pmatrix} P^{S-2}(1-P)^2 \ldots + \begin{pmatrix} S-(k+1) \\ S-M \end{pmatrix} P^k(1-P)^{S-k} = (1-P)P^k. \quad (2)$$

Finally, none of the copies of the j^{th} polyphase is received if all the corresponding M packets are lost. Therefore the corresponding probability, P_M, can be written as

$$P_M = \begin{pmatrix} S-M \\ 0 \end{pmatrix} P^S + \begin{pmatrix} S-M \\ 1 \end{pmatrix} P^{S-1}(1-P) \ldots + \begin{pmatrix} S-M \\ S-M \end{pmatrix} P^M(1-P)^{S-M} = P^M. \quad (3)$$

We can now compute the total expected distortion by adding the distortions of each polyphase component divided by total number of polyphase components, S, where $D_j(R_k)$ is the distortion of the j-th component when R_k bits are used, and σ_j^2 is its distortion when all M copies are lost. Thus, the expected distortion is

$$E[D] = \Big(\Big[\sum_{j=0}^{S-1} \sigma_j^2\Big] P^M + (1-P)\Big[\sum_{i=0}^{M-1} \Big\{P^i \sum_{j=0}^{S-1} D_j(R_i)\Big\}\Big]\Big)\frac{1}{S}. \tag{4}$$

3. OPTIMIZATION

When the expected distortion can be computed as above, our goal then is to find the best bit allocation R_i for each of the descriptions which also leads to finding the best M for a given P. Finding the best bit allocation can be stated as a constrained optimization problem, where the R_i have to minimize the distortion (4) subject to a total budget constraint, i.e., the average bit rate per sample has to be equal to the budget, R,

$$\sum_{i=0}^{M-1} R_i = R \tag{5}$$

Lagrangian optimization techniques[11,12] can be used to solve this problem by introducing a cost function, J, where a Lagrange multiplier, $\lambda \geq 0$, is used to trade-off rate and distortion. This leads to an unconstrained minimization of the cost function,

$$J = E[D] + \lambda\Big(\sum_{i=0}^{M-1} R_i - R\Big). \tag{6}$$

The optimization process can be summarized as follows. First, we set the number of polyphase components in each description, M, to be equal to maximum possible, i.e., S, which provides the maximum level of protection. Note that while each polyphase component may in general have different Rate-Distortion (RD) characteristics, here we are assuming that all the packets are structured in the same way so that copy k of any polyphase component will always be allocated R_k bits. In our experiments we further assume that RD characteristics are the same for all polyphase components. This bit allocation can be found based on either empirical RD data or closed form RD models. In both cases we use the Lagrangian optimization technique.

Consider first the optimization based on empirical data. Here we first code the source (e.g. an image in the experiments section) after performing the polyphase transform, and measure the RD values that can be achieved. Given a packet loss rate P and budget R, we iterate over a non-negative λ until we find one such that the budget is met. One particular operating point is that where the rate is zero and the distortion is the variance of the source. Thus, in the resulting bit allocation (R_i^* for $i = 0, \ldots, M-1$), if some of the copies have been allocated zero bits that means that those copies should not be transmitted and therefore that the M should be smaller. For example, if the optimal bit allocation results indicate that the rates $R_k, \ldots R_{M-1}$ should be zero, then that means that the optimal level of redundancy is $M = k$.

The same Lagrangian algorithm can also be applied when a closed-form model of the RD characteristics of the source is available. As an example, we consider the case of an i.i.d. zero mean Gaussian random source, with rate-distortion characteristic[13,14]

$$D(R) = \sigma^2 2^{-2R}. \tag{7}$$

Given that performing a polyphase transform with uniform sub-sampling will not change the rate-distortion characteristics of such a memoryless Gaussian random source, we can assume that each polyphase component has the same rate distortion characteristic of (7) (i.e. from (4), $\sigma_j^2 = \sigma^2$ and $D_j(R_i) = D(R_i)$ for all $j = 0, \ldots, S-1$). Thus, the expected distortion per sample will be

$$E[D] = \frac{1}{N}(\sigma^2 P^M + \sigma^2(1-P)\sum_{i=0}^{M-1} P^i 2^{-2R_i}) \tag{8}$$

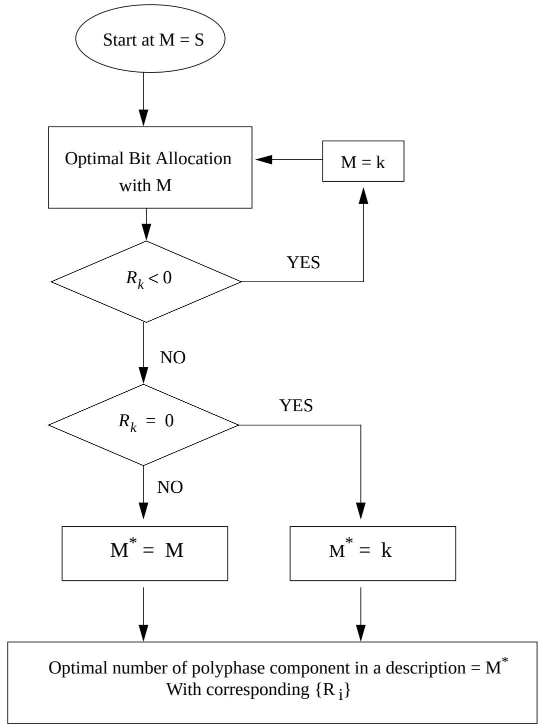


Figure 3. The algorithm flow diagram

Hence, our objective can be stated as follows:

$$Minimize \quad E[D] = \sigma^2 P^M + \sigma^2(1-P)\sum_{i=0}^{M-1} P^i 2^{-2R_i}$$

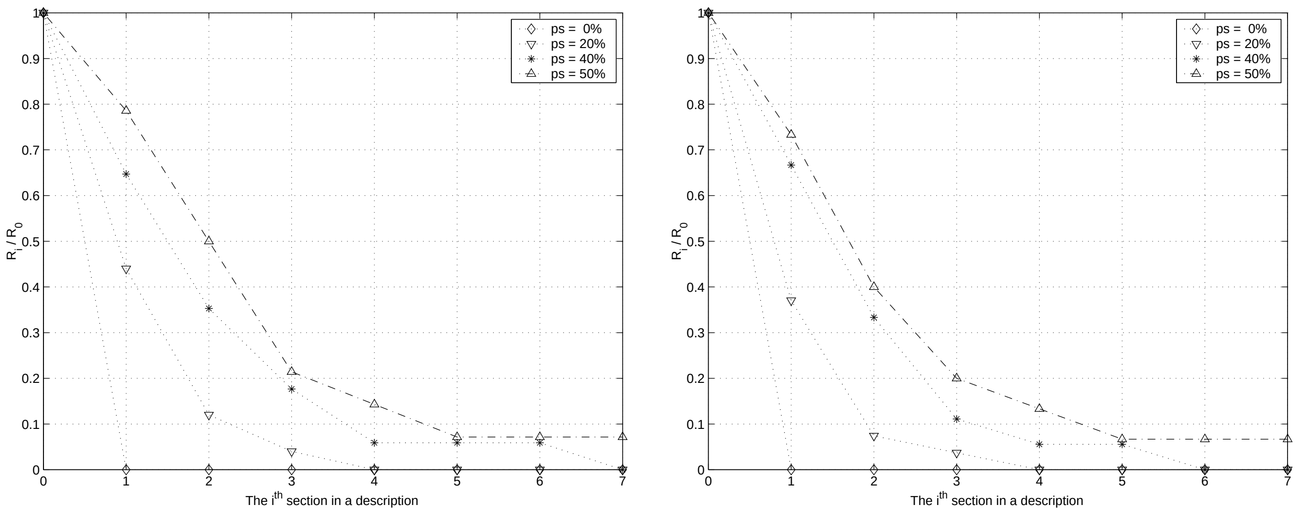
$$subject\ to \quad \sum_{i=0}^{M-1} R_i = R$$

To minimize the average distortion in the presence of channel failures, we introduce an unconstrained cost function as shown in (9) and then differentiate this constrained cost function with respect to R_i to determine λ^* and R_i^* and finally optimal bit allocation for each polyphase component in a description is derived and expressed in (10). This process is different from the empirical-based scheme in the sense that we do not need to search for the best Lagrange multiplier and the optimal bit allocation. Instead, the optimal bit allocation can be computed mathematically and directly because a closed form of a rate-distortion function of each polyphase component is explicitly assumed.

$$J = \sigma^2 P^M + \sigma^2(1-P)\sum_{i=0}^{M-1} P^i 2^{-2R_i} + \lambda\Big(\sum_{i=0}^{M-1} R_i - R\Big) \tag{9}$$

$$R_i^* = \frac{R}{M} + \frac{1}{2}\Big(i - \frac{M-1}{2}\Big)\log_2\Big(P\Big) \tag{10}$$

However, unlike the case where empirical data was used, the solutions obtained above may be such that some of the R_i^* are negative. If this is the case and, say, R_k^* through R_{M-1}^* are all negative, we would restart the optimization choosing $M = k$. This is illustrated by the the flow diagram in Figure 3.



(a) (b)

Figure 4. The redundancy allocation ratio with respect to a primary data allocation illustrated by two gray-level images, (a) lena and (b) boat when the 0^{th} section represents a primary data and the other i^{th} sections (for $i > 0$) represent redundancies

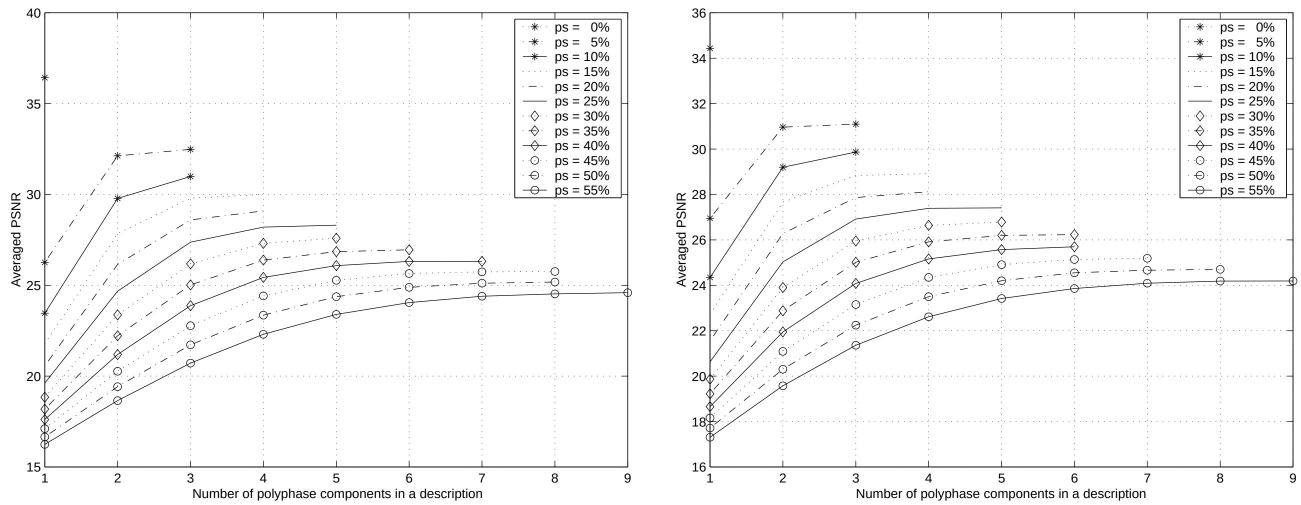
4. EXPERIMENTAL RESULTS AND DISCUSSION

In order to confirm the validity of the proposed algorithm, implementation of this algorithm in an image coding framework is performed. Our experiment is conducted with the lena and boat gray-level images of size 512×512. MDC system block diagram for this simulation is shown in Figure 1. At polyphase coder, the original input image is first decomposed in the spatial domain into S sub-images, i.e., polyphase components. In other words, our image of size 512×512 is first segmented to $\frac{512\times512}{S}$ blocks, each of size $\sqrt{S} \times \sqrt{S}$ and then we group the image pixels corresponding to the same spatial location in each block to become a polyphase component. It is worth to note that each polyphase component is considered as a sub-image of size $\frac{512}{\sqrt{S}} \times \frac{512}{\sqrt{S}}$ which allows our selected image codec to perform efficient compression (refer to an example in Figure 2.) The MDC coder produces an output bitstream with the optimal bit allocation as computed by our proposed algorithm. In this simulation, we use the empirical-based bit allocation with RD values obtained directly from the image coder.

As an image coder we use the state of art Said-Pearlman wavelet coder.[10] The SPIHT (Set Partitioning In Hierarchical Trees) codec, is used to compress each polyphase component, which forms a sub-image. This is done independently for each of the polyphase components in a description. In other words, for one description, SPIHT receives only one polyphase component at a time as its input, codes this sub-image with the optimal bit rate R_0^* obtained from our bit allocation module and produces an output bitstream. Since SPIHT is a fully embedded coder, the other copies of a given polyphase components can be obtained choosing the first R_i^* bits of the bitstream. In our experiment, the number of polyphase components is set to be 16 (i.e., $S = 16$), and we have 16 descriptions which each have the same size and a fixed bit rate budget with $R = 2$ bpp. At the receiver, for each polyphase component, the decoder will decide to use the available one that has the highest quality. However, the mean value of that polyphase component will be decided for reconstruction if no resolution is available. A simulation with a variation of the number of polyphase components in a description used as MDC system configuration is performed for analyzing performance gain using the optimal number of polyphase components in a description obtained from our proposed algorithm.

We first consider the plot in Figure 4 that represents the bit allocation characteristics for the varying description loss rates in terms of a ratio of the allocation in each polyphase component in a description to its primary information allocation. As a comparison, when the description loss rate increases, the result is a bit allocation where the relative number of bits allocated to different copies tends to be more even.

In Figure 5, we show the results when using our proposed bit allocation algorithm. Results indicate that using the



(a) (b)

Figure 5. The simulation results show a validity of using the determined optimal parameters as a MDC system configuration, illustrated by two gray-level images, (a) lena and (b) boat.

best allocation in a MDC system provides higher PSNR performance as compared with designs using an arbitrary number of descriptions. The reconstructed average PSNRs for several channel description loss rates are plotted. As intuitively expected, the optimal number of polyphase components in a description is increased as the probability that description is lost increases.

Based on our experimental results MDC system using optimal parameters outperforms ones that resort to only 2 polyphase components in a description as used in the RAT system,[9] especially at high packet loss rates. Note that in Figure 5 the curves corresponding to each packet loss rate are truncated whenever a point is reached such that no additional copies are added by the bit allocation algorithm. For example, for both images the optimal choice for a packet loss of 10% is to have $M = 3$, i.e. to transmit two redundant copies along with each primary copy.

Note that when selecting a different total number of polyphase components, S, this will lead to different bit allocations and in general different performance. As an example, we consider the performance of two MDC systems using 4 and 16 polyphase components (i.e., $S = 4$ and $S = 16$). The determined optimal level of redundancy in a description as well as the optimal bit allocation is used in this simulation to analyze the effect of the number of descriptions. In Figure 6, at low to moderate description loss rate, the 4-description system outperforms the other one, while at high loss rate the 16-description system performs better. This result is easy to explain in that the coding efficiency is reduced when going from 4 to 16 polyphase components (there is less spatial redundancy that can be exploited by SPIHT), but 16 descriptions provide increased robustness.

Finally, the proposed algorithm demonstrates how the level of redundancy can be simply adaptive without any complicated changes to transform or quantization. Given that different bit allocations should be chosen for each packet loss level, the encoder only needs to estimate the loss rates and then modify the rate selection. This will not require any changes to the decoder.

5. CONCLUSION AND FUTURE WORKS

In this paper, we investigated the problem of how to achieve a simple adaptation to changing network conditions. We give a simple analysis of how a bit allocation technique can be used to determine the optimal level of redundancy in a description. Formally, given a known channel loss rate and bit budget, the number of polyphase components to be included in a description as well as the number of bits to be used for each polyphase component in a description is determined, such that the overall expected distortion at the receiver due to both coding and description loss is minimized. Our experimental results have shown significant differences between optimal and suboptimal choices of redundancy.

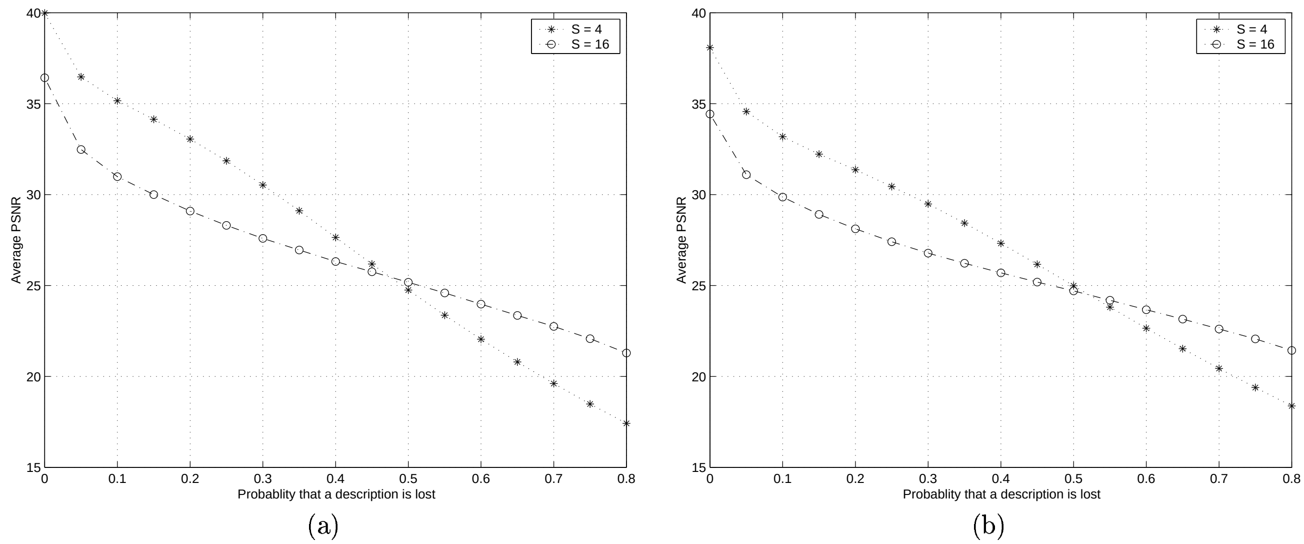


Figure 6. Performance comparison between two number of descriptions as MDC system configuration, illustrated by two gray-level images, (a) lena and (b) boat.

One interesting point should be raised in coding process. In this work, each polyphase component in a description is coded by SPIHT independently, i.e., each polyphase component in a description is coded one by one. Thus MDC system performance is expected to improve by exploiting correlation between each of the copies included in one description. Our system can also be easily extended to DCT based schemes. Finally, we also plan to generalize our approach so that different levels of redundancy are applied to different frequency components.

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