MULTIPLE DESCRIPTION CODING OF IMAGES USING PHASE SCRAMBLING

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ABSTRACT

Phase scrambling as discussed in this paper, spreads the information in each pixel of an image among virtually all the pixels of the resulted scrambled image. This property can be exploited in multiple description coding of images where the loss of one or many descriptions is a common case. In this paper, we employ phase scrambling, as a form of all-pass filtering to mix the information of each pixel with all the pixels of the image, followed by decomposing the scrambled image into multiple descriptions. Our experiments show that this technique is competitive to other proposed methods such as Lapped Orthogonal Transforms. Phase scrambling as suggested in this article does not produce localized visual artifacts such as ringing and blocking effects and does not require complex post-filtering to yield acceptable reconstruction quality. Another advantage of phase scrambling is that the scrambling can be implemented in hardware and be performed in real time.

1. INTRODUCTION

As a joint source-channel coding method, multiple description coding (MDC) has many applications in transmission of images over unreliable packet or multiple path networks that cannot guarantee lossless data delivery. Forming multiple descriptions of an image, that satisfy both constraints of good perceptual quality and optimal bandwidth (bit rate) consumption has been a very interesting research area for the last decade [1].

The most prominent suggested methods for MDC of images can be divided into three main groups. The first group suggest decorrelating the samples of the image (pixels) using an energy-compacting transform (DCT, DWT,…), then adding the required amount of correlation between the coefficients using a correlating transform such as Pairwise Correlating Transforms [3, 4]. The second group suggest using Lapped Orthogonal Transforms (LOT) [2, 11]. The third main group use MD quantizers that produce more than one output sequence [5, 6].

The main advantage of these methods is that the amount of redundancy between the descriptions can be controlled. The disadvantage is that they require complex computations for coding and decoding, which makes them extremely hard to implement in practical applications. The performance of the methods based on MD quantization relies on the stationarity of images, which makes them inapplicable to a general purpose application.

In our proposed method, we distribute the information of each pixel among all the pixels in the image by passing the image through an all-pass filter. This is in effect equivalent to performing a circular convolution of the image with another matrix which only affects the phase of the frequency components, hence the name "Phase Scrambling". We then quantize, decompose and encode the scrambled image using a compression method. A similar method has been proposed in [7] for increasing robustness to channel noise.

In the remaining sections of this paper, we provide some details about phase scrambling discuss the setup of a simulation experiment and also compare the performance of our system with the works of D.M. Chung and Y. Wang [2], and comment on issues associated with performance and implementation of our proposed method and existing methods for MDC.

2. PROPOSED METHOD

2.1. Phase scrambling and unscrambling

In order to increase the robustness over the loss of a description or a part of image data, we suggest using the circular convolution of the image with a matrix called the "Key", then decomposition and coding. The Key is a signal with random phase and unit magnitude. In order for the Key to be real, the only requirement is that its phase must have odd symmetry. In practice, the Key can be produced by generating a random matrix the same size as the image, taking its Fourier transform, setting the magnitude to unity, and taking the inverse Fourier transform of the result.

If we present the N×N input image as **F**(i, j) and the key matrix as **K**(i, j), the circular convolution of the key and the image will be a matrix **R** defined as

$$R(m,n)=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}K(m-i,n-j)_c F(i,j)$$

where

$$K(i,j)_c = K(i \bmod N, j \bmod N)$$

As can be seen, each pixel of **R** is a weighted sum of all the pixels of the input image. In practice, the circular convolution operation is performed by taking the Fourier transform of the two operands, multiplying them element by element and taking the inverse Fourier transform. This way, all the process requires $O(N^2\log_2 N)$ floating point operations [8]. For unscrambling, the same process is followed, but with the only difference that the Fourier transform of the key is complex conjugated and multiplied by the Fourier transform of the scrambled image. This operation is equivalent to computing the circular correlation of the scrambled image with the modulo-N shifted Key matrix for an N×N image. In hardware implementation of phase scrambling, the real Key matrix is not used. Only half of the phase components of its Fourier transform are needed and must be stored and the other half can be derived.

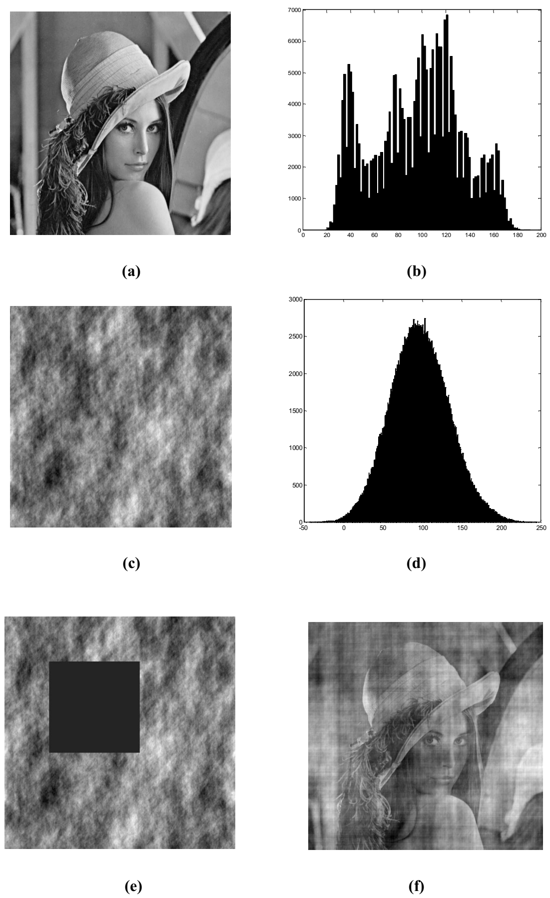

Figure 1: **(a)** The 512×512 Lena image. **(b)** Histogram of (a), $\mu = 96.8$, $\sigma^2 = 1394.6$
(c) Lena scrambled. **(d)** Histogram of (c) $\mu = 96.8$, $\sigma^2 = 1394.6$
(e) (c) with 15% pixels lost. **(f)** (e) unscrambled , PSNR ≈ 17.5 dB

Phase scrambling, as depicted above, does not alter the mean, variance and covariance matrix of the input image. The scrambler is basically an all-pass filter, and all-pass filtering does not alter the above metrics. Therefore, the scrambled image has the same energy distribution, pixel-to-pixel correlation and the same mean as the original image. A very important fact is that because of the weighted summation operation being applied on all the pixels, the probability distribution of the scrambled image is a very good approximation of the Gaussian distribution, with the same mean and variance of the input image. This is a very interesting result, since it provides a universal probability model for the set of scrambled images and can be used in design of quantizers and compression algorithms.

In figure 1, we have shown the histogram of image Lena, its scrambled version, and the increased robustness of the scrambled Lena to loss of data, by setting a 200×200 window (approximately 15%) of its pixels to zero, and unscrambling it. Phase scrambling distributes the localized loss over the entire image, and provides a reconstruction with less visual artifacts than when the loss has been added to the original image.

2.2. Signal decomposition

In order to make four descriptors of the scrambled result, even-odd separation is used. First description contains the (even, even) indexed samples, second description contains (even, odd) samples, and so on. For making two descriptions, we have grouped (even, even) and (odd, odd) pixels in one description, and (even, odd) and (odd, even) pixels in the other description.

2.2. Compression

Since the scrambling does not alter the energy distribution of the image and the correlation of the pixels, any energy-compacting, context-based or entropy coding method can be applied to the descriptors. We have experimented Embedded Zero-tree Wavelet (EZW) [9] compression and Huffman coding of the quantized scrambled image and both family of compression algorithms have provided acceptable results. The advantage of using embedded compression such as SPIHT [10] or EZW is that even in case of receiving a fraction of one description's bit stream, the received bits can be used to form the descriptor and improve the quality of reconstruction. The block diagram of a communication system with phase scrambling is shown in figure 2.

3. SIMULATOIN EXPERIMENT

3.1. Experiment setup

In order to compare phase scrambling with other existing methods for MDC, we have simulated a system as in figure 2 working with the 512×512 image Lena.

The Key has been produced by taking the Fourier transform of a completely random matrix of the same size as the Lena image, setting the magnitude of it to 1, and taking the inverse Fourier transform of the resulted matrix. The circular convolution operation is performed by element-by-element multiplication of the by the Fourier transform of Lena. The complex conjugate of the phase of the key matrix is used for unscrambling. The scrambled image is quantized and decomposed as depicted in section 2.2.

In one experiment with emphasis on low bit-rates, we have first quantized the scrambled Lena using an 8-level quantizer, decomposed in into four descriptions, and coded each descriptor using an EZW coder with Daubechies-6 wavelet bases and four levels of wavelet transformation. The channel bit rate is the bit rate of the EZW coder.

At high bit rates (e.g. higher than 1.5 bpp), we have simply used quantization followed by entropy coding. In this case, the bit-rate is controlled by the levels of the quantizer and the average code word length of the entropy coder used. We have used a non-uniform quantizer with different levels and Huffman coded the quantized data. Because the scrambled images have Gaussian-like distribution, the quantizer boundaries have been optimized for Gaussian input with same mean and variance as the original Lena image. Here, we have taken advantage of Gaussian distribution of the pixel values of scrambled image. There is no need for on-line training of the quantizer for achieving satisfactory results.

In reconstruction of the scrambled image, we have taken advantage of the unchanged pixel-to-pixel correlation in the scrambled image, and substituted the pixels from lost descriptions with the average of the surrounding pixels from received descriptions.

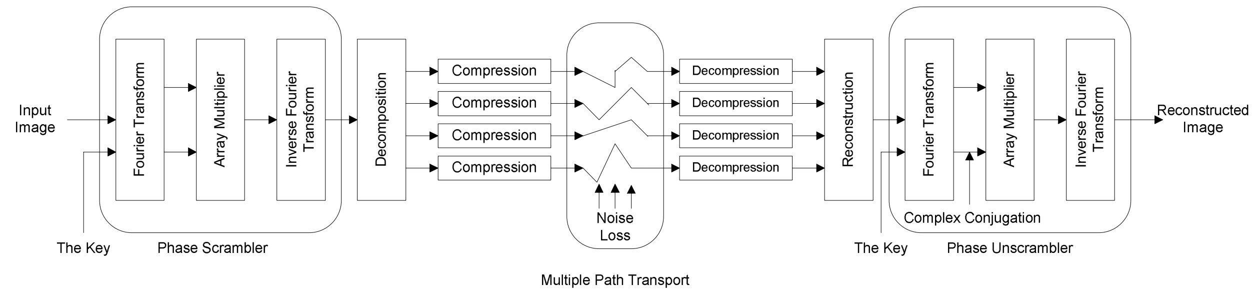

Figure 2: Block diagram of a communication system with MDC and phase scrambling

3.2. Experiment results and comparison

In our experiment with low channel rates, we decomposed the scrambled Lena image using even-odd separation into four descriptions and coded each description separately with the EZW coder. We have compared our results with the reported results of Chung and Wang using LOT [2].

Figure 3 shows the rate distortion curves of our experiment and results of Chung and Wang's experiments with T9 LOT basis [11] which they suggest to have the "lowest coding efficiency but the best reconstruction performance"[2]. In the case of four descriptions, we have also provided the results for coding the image Lena using the same EZW coder without any decomposition or scrambling.

MDC using phase scrambling outperforms LOT by 4 dB at low rates and 4.5 dB at higher rates for one description, and stands an average 2 dB above LOT in reconstruction with two, three and four descriptions. In the case of four descriptions, the result of the single description EZW coder is an average 7 dB better than phase scrambling and 9 dB better than T9 LOT.

In the case of MDC with LOT, the reconstruction quality with direct inverse LOT is very poor. The presented results have been produced using an iterative maximally-smooth recovery numerical algorithm after taking the inverse LOT [2]. MDC with phase scrambling does not require any such post-processing.

Figure 4 shows two reconstructions of image Lena at 0.5 bpp channel rate with different numbers of received descriptions. At this low bit rate, the reconstruction PSNR does not improve much as more descriptions are received. The interesting point in this figure is the absence of ringing effects at low rates, due to the distribution of localized noise as stated in section 2.1.

In our second experiment we have quantized the scrambled Lena using a non-uniform quantizer with different number of levels. The levels of the quantizer have been set assuming a Gaussian distribution with the same mean and variance as the input image. The quantized image is then decomposed to form two descriptions and quantizer indexes of each description have been Huffman coded. At high bit rates, the performance of this system is acceptable. Figure 5 shows the results of this experiment.

Unfortunately we were unable to find a similar experiment with reported rate-distortion results in the literature to compare with our work. Authors of [5, 4, 6, 3] base their experiments on redundancy rate-distortion curves, and do not comment on the reconstruction quality of their proposed method versus consumed bit rate in a rate-distortion sense. In figure 6, we have shown reconstructions of Lena image using this technique at 2.1 bpp.

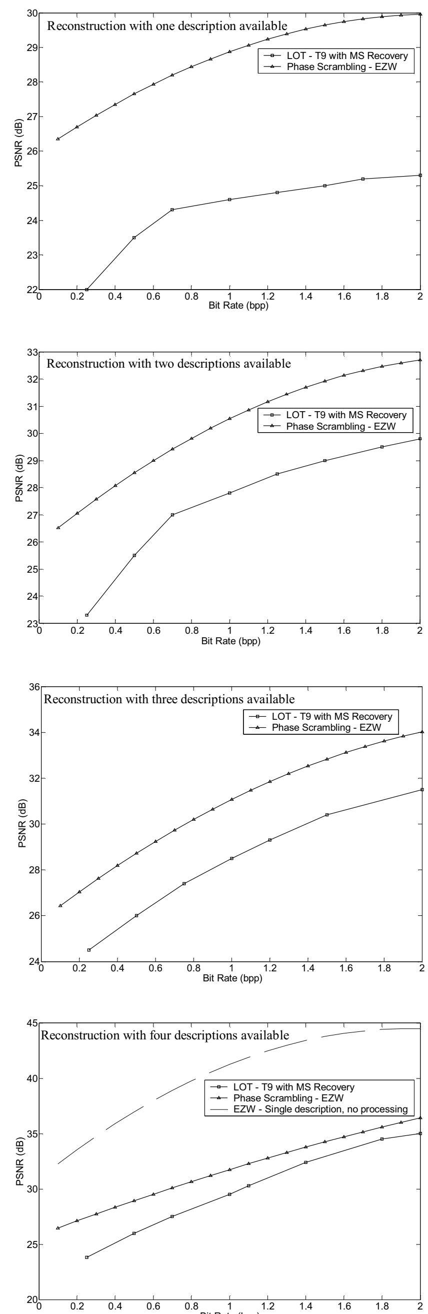

Figure 3: Rate-distortion curves for the MDC system with Phase Scrambling/EZW and with LOT for one, two, three and four received descriptions.

Figure 4: Reconstruction of Lena using Phase Scrambling and EZW at 0.5 bpp. The above row contains reconstruction with one (PSNR ≈ 28.3 dB) and two (PSNR ≈ 29 dB) descriptions. The lower row contains reconstructions with three (PSNR ≈ 29.1 dB) and four (PSNR ≈ 29.4 dB) descriptions.

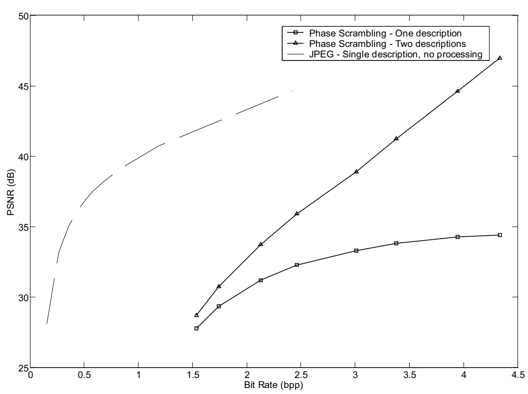

Figure 5: R-D curves of the MDC system using Phase Scrambling /Huffman Coding at high bit rates.

Figure 6: Results of reconstruction of Lena at 2.1 bpp when quantizing and Huffman coding has been used. The left image is reconstruction with one description (PSNR ≈ 31.2 dB). The right image is reconstruction with two descriptions (PSNR ≈ 33.7 dB

4. CONCLUSION

In this paper we propose a method for multiple description coding of images based on phase scrambling. Phase scrambling, as a form of all-pass filtering, mixes the information of each pixel with all the pixels of the image, but does not change the energy distribution or the covariance matrix of the input image. The scrambled image is then decomposed into multiple descriptions and each description is coded separately.

Phase scrambling outperforms the best LOT method by 4-4.5 dB at one description and 2 dB at higher descriptions.

The proposed method is extremely flexible, since it is energy-preserving and independent of the compression algorithm. It can also be implemented in hardware and performed in real time. In addition, phase scrambling provides robustness to additive noise and localized losses and reduces irritating visual artifacts such as ringing and localized loss by distributing its effect on all image pixels.

5. REFERENCES

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