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Color Image Wavelet Compression Using Vector Morphology

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ABSTRACT

In this paper we explore a wavelet compression scheme for color images that uses binary vector morphology to aid in the encoding of the locations of the wavelet coefficients. This is accomplished by predicting the significance of coefficients in the sub-bands. This approach fully exploits the correlation between color components and the correlation between and within sub-bands of the wavelet coefficients. This compression scheme produces images that are comparable in quality to those of color zerotree tree encoders at the same data rate but is computationally less complex.

1. INTRODUCTION

The wavelet transform has been successfully used in image coding since it allows localization in both the space and frequency domains [1, 2, 3]. Coders can then exploit the characteristics of the wavelet coefficients to achieve better efficiency. Successful approaches such as the zero-tree method introduced in 1993 by Shapiro [3], exploit the fact that the wavelet coefficients are correlated across sub-bands. This takes advantage of the *inter-band* dependencies of the wavelet coefficients, based on observation that there is a high correlation between the magnitudes of the coefficients from different sub-bands, corresponding to the same spatial location of the image.

In [4, 5] *intra-band* dependencies of the wavelet coefficients are also exploited. There is concentration of energy around a neighborhood of the coefficients in a given sub-band when edges occur in the image, thus allowing for the prediction of the locations of these clusters within the sub-band. To exploit these dependencies, the prediction is done using a region growing approach. The inter-band dependencies are exploited by using morphology based prediction. The performance of this method is comparable to that of zerotree coders but is less complex. This work was extended and improved in [6] by the use of wavelet packets. Both of the techniques were developed for gray-scale images.

In this paper we extend this approach to color images by concentrating on the use of predictors for sub-bands across different color components based on binary vector morphology.

Section 2 of this paper describes the principles behind binary morphology and how it can be extended to binary vectors. In Section 3, these filters are then used to encode the location of significant wavelet coefficient. Section 4 presents our experimental results.

2. BINARY MORPHOLOGY

Morphological filters are nonlinear signal operators that locally modify the geometrical features of a signal. Given a binary image X, and a 2-D binary structuring element B, the *dilated* image is defined as the union of all the pixels that fall under B when it is centered at each pixel in X [7]. The *eroded* image is similarly defined as the intersection of pixels that fall under B when centered at each pixel in X.

Given a vector valued binary image $\boldsymbol{Y}$, morphological filtering can be defined by using component-wise operators [8]. In this case, the structuring element can then be different for each component. The concept of morphological vector filters can be extended by using a scalar valued function that maps each vector $\boldsymbol{y_i}$ to a scalar value d_i. In our case, for a three component binary valued vector the mapping is $d{:}\{0,1\}^3 \rightarrow \Re$ [9]. Dilation is then the binary valued vector under the structuring element that has maximum d, and erosion would similarly, be the vector with the minimum d. Observe that different choices of d can potentially lead to different results. The

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component-wise approach for vector valued images is generally referred in the literature as marginal ordering, and the approach using the mapping is known as reduced ordering [9, 10].

3. COLOR MORPHOLOGY CODER

A *significace map* is a binary representation of the "significance" of the wavelet coefficients relative to a given threshold. All coefficients that are greater than the threshold are said to be significant. The significance map can be thought of as a mask that indicates to the decoder the location of these "significant coefficients." While Shapiro encodes a series of these maps using zerotrees, in [4] a method for encoding a gray scale image is proposed by predicting the significance map of higher sub-band coefficients based on the significance of coefficients from lower sub-bands. This approach exploits the inter-band dependencies of the significant coefficients. The prediction of higher sub-band significance maps is done using binary morphological filters. The significance map for the lower sub-bands (coarser scale) needs to be encoded so that the higher sub-band significance maps can then be predicted. The lower sub-bands are encoded by using a region growing method, exploiting the intra-band dependencies of the sub-band, the prediction of the other sub-bands is obtained by using binary morphological filters.

It is well known that the RGB components of color images are highly correlated. If the wavelet transform of each color component is obtained, the transformed components will also be highly correlated. Therefore, a color transformation that reduces the psychovisual redundancy and correlation of the image is highly desired [11]. Many such linear transformations can be used such as the YUV, KLT, YCrCb or La*b*.

Figure 1 shows the significance map of the Y, U and V components of the *Girl* image. In the significance map, the white regions represent the location of significant coefficients. In this paper we extended the prediction methods described above to also exploit the spectral correlations of the significant coefficients using a "color" significance predictor based on binary vector morphology.

In order to understand how our Color Morphology Coder (CMC) works it is important to understand that the objective behind our coder is to encode the location of wavelet coefficients that are significant. The basic idea behind this algorithm can be summarized as follows: first a color transformation is performed in order to decorrelate the color components as described earlier. This is followed by a wavelet transformation and a uniform quantizer. The quantizer is chosen so that a desired data rate is achieved. Figure 2 shows the block diagram of the CMC system. The DC coefficients of all three wavelet coefficient components are encoded separately. The rest of the coefficients are encoded from coarse to fine scales with each color component image treated separately (region growing and prediction is not done across the color components). The lower sub-bands are then encoded independently using a region-growing algorithm described in [6] consisting of scanning a neighborhood of significant pixels and growing this neighborhood iteratively as long as it includes significant pixels. In order to start the prediction of the higher order sub-bands, a structuring element and a vector morphological filter need to be chosen as described in Section 2. What the morphological filters are doing is enlarging or reducing the area where one should scan (the prediction indicates where is the most likely location of a significant coefficient) for significant coefficients. All coefficients not covered by the prediction maps need to be encoded separately.

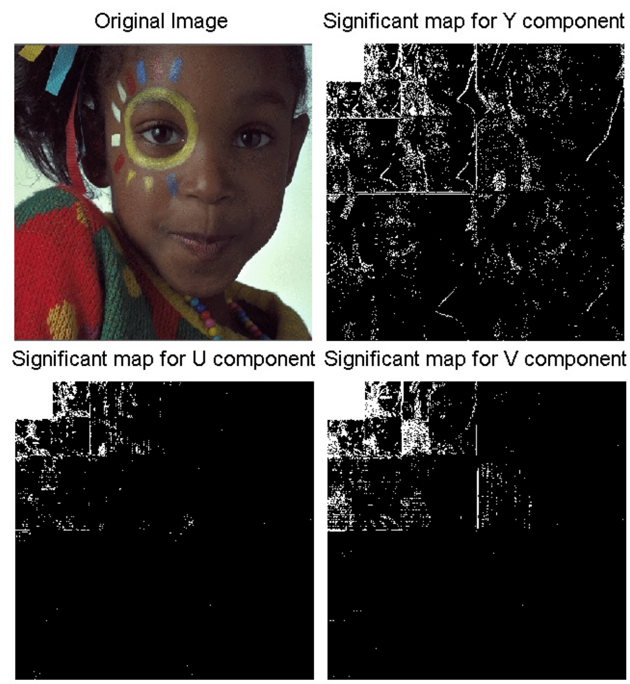


Figure 1 *Girl* image and significant map of quantized wavelet coefficients for the Y, U and V color components

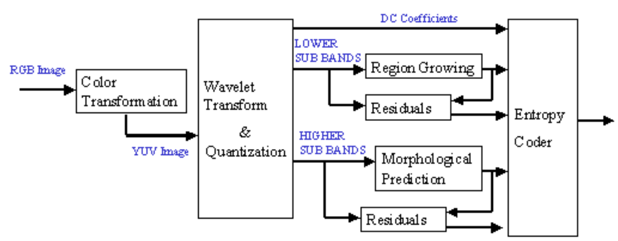


Figure 2. Block diagram of the CMC system

4. EXPERIMENTAL RESULTS

A set of 512x512, 24 bit RGB images were compressed using CMC to a fixed data rate (given in bits per pixel) and compared to images compressed by SPIHT [12] .

The color transformation used in this experiment was the YUV color transformation as given in [11]. A five level wavelet decomposition, based on the 9/7 biorthogonal wavelet filter described in [2] was used for all the test images. This was followed by a uniform quantizer. The DC coefficients are coded separately for the three color components as described in the previous section. After encoding through region-growing the lower sub-bands, the higher sub-bands prediction is performed by using marginal ordering dilation (see Section 2). The prediction errors are also encoded. All this information is further entropy coded.

The peak signal-to-noise ratio (PSNR), based on mean square error (MSE), is used as a measure of "quality". The PSNR of a color image with color components R, G, and B is given by:

$$\text{PSNR} = 10\log_{10}\left(\frac{255^2}{\frac{MSE(R)+MSE(G)+MSE(B)}{3}}\right) \quad (1)$$

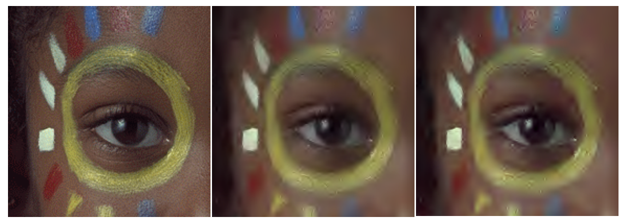
Table 1 shows the PSNR of three images, encoded at different data rates varying from 0.15 to 0.6 bits per pixel (bpp). For all images CMC performed comparable to SPIHT, the *Girl* image encoded at 0.15 bpp is shown in Figure 3. Figure 4 shows an enlarged region of the image in order to better see the coding artifacts. Figure 5 and Figure 7 show the *Motorcycle* and the *Barbara* image encoded at 0.4 and 0.2 bpp respective. A region of these images was selected and it is shown in Figure 6 and Figure 8.

	Barbara		*Girl*		*Motorcycles*	
	bpp	PSNR	bpp	PSNR	bpp	PSNR
CMC	.4	26.04	.15	27.54	.4	25.85
SPIHT		26.81		28.36		26.34
CMC	.5	26.65	.22	28.36	.6	24.32
SPIHT		27.36		29.08		24.93

Table 1. PSNR for images compressed to different bit rates with our CMC and SPIHT.

(a) (b)

Figure 3. *Girl* image compressed to 0.15bpp using (a) CMC and (b) SPIHT

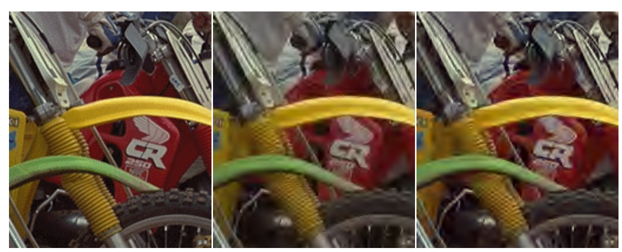


(a) (b) (c)

Figure 4. Eye detail in *Girl* image (a) original, (b) CMC 0.15bpp (b) SPIHT 0.15bpp.

(a) (b) (c)

Figure 5. *Motorcycle* image (a) original, (b) CMC 0.4 bpp (b) SPIHT 0.4 bpp.

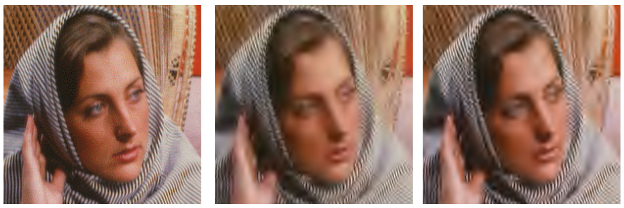


(a) (b) (c)

Figure 6. Detail in *Motorcycle* image (a) original, (b) CMC 0.4 bpp (b) SPIHT 0.4 bpp.

(a) (b) (c)

Figure 7. *Barbara* image (a) original, (b) CMC 0.2 bpp (b) SPIHT 0.2 bpp.



(a) (b) (c)

Figure 8. Face detail in *Barbara* image (a) original, (b) CMC 0.2 bpp (b) SPIHT 0.2 bpp.

5. CONCLUSIONS AND FUTURE WORK

An extension to previous work in gray scale image coding using morphological based prediction was presented. The correlation between color components, between significance of wavelet coefficient within and across sub-bands was exploited in our coder. Images compressed with CMC had comparable quality, both qualitatively and quantitatively, to those coded with traditional zerotree based coders.

CMC can be further integrated with progressive encoding so that an embedded bit stream can be generated. Performance can also be improved by using wavelet packets. The use of different structuring elements and prediction methods that further exploit the redundancy in the color bands may also improve the performance.

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