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Multiwavelet-based Image Compression Using Human Visual System Model

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Abstract. Multiwavelet has some important properties such as orthogonality, symmetry, and short support, which make up for the shortcoming of scalar wavelet. In this paper, we consider the problem of improving the performance of multiwavelet-based image coders combining human visual syetem (HVS). By taking into account the imperfections inherent to the HVS, HVS weighting is designed to achieve higher compression rate and minimizing distortion due to compression. After multiwavelet transform, coefficients in different subbands are weighted directly by the band-average of the contrast sensitivity function (CSF) curve in the normalized spatial frequency domain, at last multiwavelet-based set partitioning in hierarchical trees (MSPIHT) algorithm is used to code forming embedded bit stream. Experimental results showed our proposed image compression algorithm can get better subject visual quality than the conventional MSPIHT algorithm at the same compression ratio.

Keywords: Image compression; human visiual system (HVS); multiwavelet transform; set partitioning in hierarchical trees (SPIHT)

1. Introduction

One of the most challenging problems for the development of a visual communication system is that the available bandwidth of the networks is usually insufficient for the delivery of the voluminous amount of the image data. Designing a visual coding system is a complicated task. Depending on the application, there are many issues related to the performance of the image codecs, such as quality-compression computational complexity, memory requirement, parallelizability, scalability, robustness, security and interactivity. Although the image coding standards (e.g., JBIG, JPEG and JPEG2000) exhibit acceptable quality-compression performance in many visual communication applications, further improvements are desired and more features need to be added, especially for some specific applications.

Over the past few years, there has been an increasing number of research activities on multiwavelets, both in pure mathematics as well as engineering applications. Such growing interests in multawavelets mainly stem from the following facts[1,2]: (i) multiwavelets can simultaneously posses orthogonaliry, symmetry, and a high order of approximation for a given support of the scaling functions (this is not possible for any realvalued scalar wavelet); and (ii) multiwavelets have produced promising results in the areas of image compression and denoising.

At the meanwhile, the research trend is to incorporate Human Visual System (HVS) models into the coding system. It is well accepted that perceived image quality does not correlate well with peak signal-to noise ratio (PSNR), which is still the most widely used method for image quality evalution. HVS characteristics must be considered to provide better visual quality measurements.

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Our work stands at the intersection of the two promising research trends. This paper is organized as follows. In Section II, we briefly review the basic notions of multiwavelet theory. Section III introduces the human visual system characteristic and Section IV proposes a muiltiwavelet-based coding method combing HVS weighting. In Section V we present the compression results obtained from the application of three multiwavelet bases to classical test image and we make some comparison with those compressed results without HVS. Section VI provides a summary and conclusion to the paper along with suggestions for future work in this area.

2. Multiwavelet Transform

Now we introduce some basic theory and notations to be used throughout this paper. Just as in the scalar wavelet case, the theory of multiwavelets is based on the idea of multiresolution analysis (MRA). The difference is that standard multiresolution has one scaling function $\boldsymbol{\Phi}(t)$, however the multiwavelets have several scaling functions. For a multiwavelets system with N scaling functions, the vector $\boldsymbol{\Phi}(t) = [\phi_1(t), \phi_2(t), \cdots, \phi_N(t)]^T$ is a compactly supported orthonormal scaling vector of length N generating a MRA[3,4,5].

The translates $\boldsymbol{\Phi}(t-k)$ are linearly independent and produce a basis of the subspace $V^{(0)}$. The dilate $\boldsymbol{\Phi}(2^j t - k)$ of $\boldsymbol{\Phi}(t-k)$ generate subspaces $V^{(j)}, j \in Z$, such that

$$\cdots \subset V^{(-1)} \subset V^{(0)} \subset V^{(1)} \subset \cdots \subset V^{(j)} \subset \cdots$$

$$\bigcup_{j=-\infty}^{\infty} V^{(j)} = L^2(R) \qquad \bigcap_{j=-\infty}^{\infty} V^{(j)} = \{0\}$$

Associated with $\boldsymbol{\Psi}(t)$ is a multiwavelets function vector $\boldsymbol{\Psi}(t) = [\psi_1(t), \psi_2(t), \cdots, \psi_N(t)]^T$, such that its translates $\boldsymbol{\Psi}(t-k)$ are linearly independent and produce a basis of the "detail" subspace $W^{(0)}$, where $W^{(0)}$ is the orthogonal complement of $V^{(0)}$ in $V^{(1)}$, $V^{(1)} = V^{(0)} \oplus W^{(1)}$.

The multiscaling functions vector $\boldsymbol{\Phi}(t)$ satisfy a matrix dilation equation (similar to the scalar case)

$$\boldsymbol{\Phi}(t) = \sqrt{2}\sum_k C[k]\boldsymbol{\Phi}(2t-k) \tag{1}$$

The coefficients $C(k)$ are $N \times N$ matrices.

The multiwavelets functions vector $\boldsymbol{\Psi}(t)$ satisfy a matrix wavelet equation

$$\boldsymbol{\Psi}(t) = \sqrt{2}\sum_k D[k]\boldsymbol{\Phi}(2t-k) \tag{2}$$

The coefficients $D(k)$ are also $N \times N$ matrices.

Analogous to the discrete wavelets case, we can elicit the fast transition algorithm for DMWT:

$$V_k^{(j)} = \sum_n C[n-2k]V_n^{(j+1)} \tag{3}$$

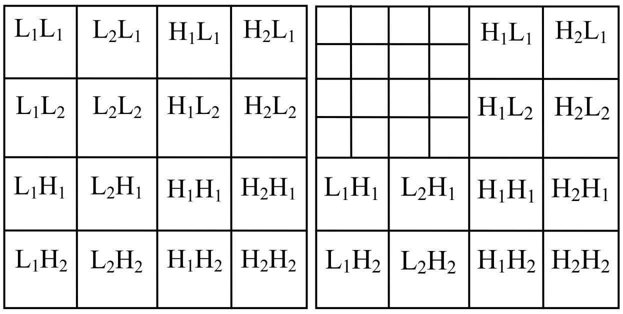
$$W_k^{(j)} = \sum_n D[n-2k]V_n^{(j+1)} \tag{4}$$

Corresponding reconstruction algorithm is following:

$$V_k^{(j+1)} = \sum_n V_n^{(j+1)}C[k-2n] + \sum_n W_n^{(j)}D[k-2n] \tag{5}$$

Similar to the scalar wavelet case, corresponding to each multiwavelet system is *N*-channel matrix-valued filterbank, or multifilter with filter "taps" that are $N \times N$ matrices (in this paper, we will be working with $N = 2$).

Fig.1 shows the image decomposition by multiwavelet transform by one-level and two-level.



(a) one-level decomposition (b) two-level decomposition

Figure 1. Multiwavelet decompisition of image

3. Agnalysis of Human Visual Syarem

Over the years, through the eyes of some visual phenomena were observed, and the combination of visual physiology, psychology and other aspects of research, the researchers have found a variety of visual masking effect. If we can make full use of the human visual masking effects during image encoding process, you can allow more actual image distortion in the same subjective quality condition. According to Shannon theory, using lower bit rate to code images may obtain less bad objective quality while remaining the subjective quality unchanged. The results show that: (1) the human eyes are very sensitive to distortion of the edges of image; (2) the eyes are sensitive to the distortion of smooth field in the images; (3) the human eye are not sensitive to the distortion of the textures in the images[6,7].

The contrast sensitivity function (CSF) describes humans' sensitivity to spatial frequencies. A model of the CSF for luminance (or grayscale) images, originally proposed by Mannos ans Sakrison, is given by[8,9]:

$$H(f) = 2.6(0.192 + 0.114f) \cdot \exp[-(0.114f)^{1.1}]$$

where spatial frequencies is $f = \sqrt{f_x^2 + f_y^2}$ with units of cycles/dgree. And f_x, f_y are the spatial frequencies in the horizontal and vertical directions respectively.

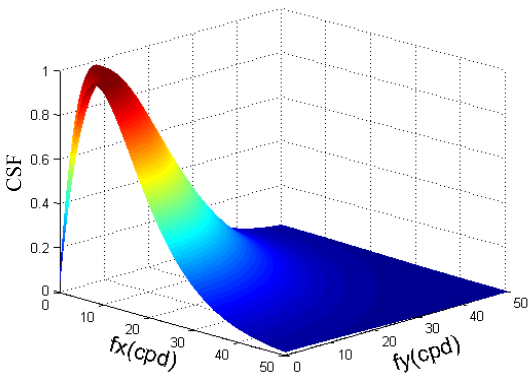


Figure 2. 2D CSF curve.

Form the figure above, we can see that the information in low and middle frequency subbands are more important than those in the high frequency subbands, this is consistent to the distribution of different fields in the images. In transform domain, the smooth fields distributed in low frequency subband and textures information distributed in high frequency subbands. According to importance of frequency of CSF, weighing transform coefficients with different parameters can give more bits to the domains which are sensitive to the human eyes and fewer bits to those which are less sensitive to the human eyes.

4. Multiwavelet-based Coding Combining HVS

As we all know, SPIHT[10] algorithm presented by A. Said and W.A. Pearlman utilized the parent-offspring dependencies as defined in spatial orientation-tree (SOT) and ordered bit plane with a set partitioning sorting algorithm to obtain better compression performance than embedded zerotree wavelet

(EZW) coding[11]. However, multiwavelet transform is applied to images, multiwavelet coefficients cannot establish parent-children relationship defined in SPIHT algorithm. Though shuffling[12,13,14], rearrange the multiwavelet coefficients corresponding to the same position in high frequency subbands. Then multiwavelets coefficients can be quantized and coded by SPIHT algorithm to generate embedded bit stream as called MSPIHT algorithm.

In our proposed method, multiwavelet coefficients are weighted before MSPIHT coding. A band-average CSF mask gets its weights directly from the CSF curve in the normalized spatial frequency domain. Each CSF weight is computed as the average of the CSF curve in its corresponding frequency band. All of the weights are normalized such that smallest is one. For a five-level multiwavelet decomposition of the image, the band-average CSF mask is a 6-weight mask. The weight parameters are 1.79, 2.35, 2.87, 3.16, 2.56 and 1.00 form low frequency band to high frequency band.

The flowchart of MSPIHT+HVS is shown in Fig. 3.

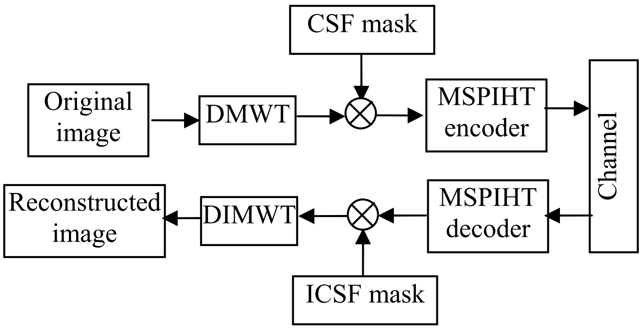


Figure 3. The flowchart of MSPIHT+HVS

5. Experimental Results and Analysis

In our image compression scheme we employ sa4, cl and ghm multivawavelet bases. This is followed by MSPIHT and MSPIHT+HVS. We compare the results with the performance of the biorthogonal scaler wavelet db9/7 which has a vanishing order of 4 for its analysis and synthesis wavelets.

PSNR is the standard method for quantitatively comparing a compressed image with the original one. The PSNR values are tabulated in Table I for standard test image barbara. At the same bit rate, multiwavelet-based algorithm can obtain comparable performance. At low bit rate the method with HVS weighting is lower than those without HVS weighting 1~2dB and at high bite rate the two methods performance are almost the same.

Fig. 4(a) show the original image and Fig. 4 (b), (c), (d) are reconstructed images by different coding methods at 0.25bpp. From Fig. 4(b) and (c), we can see MSPIHT keep more texture in tablecloth than SPIHT, that is to see multiwavelet transform is more suitable to keep high frequency information than wavelet transform in image compression. From Fig. 4(c) and (d), MSPIHT+HVS can obtain better visual quality than MSPIHT.

Table 1 Comparison of PSNR (dB) with Different Coding Methods

Base	Method	1.0bpp	0.5bpp	0,25bpp	0.125bpp
db 9/7	***SPIHT***	35.5250	30.3316	26.4019	23.7939
	MSPIHT+HVS	34.0482	28.5960	25.0435	23.6756
sa4	***MSPIHT***	34.7401	29.6493	26.2593	23.7240
	MSPIHT+HVS	33.3620	28.7468	25.4863	23.7109
cl	***MSPIHT***	33.5457	28.6764	25.4272	23.3501
	MSPIHT+HVS	32.4200	27.9044	24.8491	23.3322
ghm	***MSPIHT***	33.0164	28.2452	252621	23.4583
	MSPIHT+HVS	30.7819	26.9092	24.5346	23.3210

(a) original image (b) db9/7(SPIHT)

(c) sa4(MSPIHT) (d) sa4(MSPIHT+HVS)

Figure 4. Recontructed images by different coding methods.

6. Conclusions

Multiwavelet is a new theory of wavelet construction. Its excellent propertied have gradually attracted researchers' and engineers' interesting. We present our recent work on multiwavelet-based coding algorithm combining human visual system model. Experimental results suggest the proposed method yields better subjective visual performance and keep more texture information than MSPIHT at the same compression rate. More study is to be done on design of weight parameters. Further results of the special application of the 2D multiwavelets in image compression will be presented elsewhere.

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