Embedded Image Coding Based on Context Classification and Quadtree Ordering in Wavelet Packet Domain

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ABSTRACT

This paper presents an embedded wavelet packet image coding algorithm which is based on context classification and quadtree ordering (CCAQO). To match up well with the quadtree-based embedded coder, a new cost function for the best basis selection is adopted in discrete wavelet packet transform (DWPT). In addition, combined with the structure of the best wavelet packet basis, a complete quadtree representation of wavelet packet coefficients is established to explore the ordering procedure of embedded image coding. Since subband correlation is mainly captured by significance coding, our focus is on significance coding. The significance probability of wavelet coefficient is estimated by convoluting a 9×9 FIR filter matrix kernel with the significance states of neighboring coefficients, and then a context classifier based on Lloyd-Max algorithm is used to categorize the wavelet coefficients with the same or similar significance probability into several contexts. The significance state of wavelet coefficient with respect to a given threshold is encoded using adaptive arithmetic coder based on the classified context. Due to the optimal context classifier and the flexible quadtree representation ability of wavelet packet coefficients, the proposed CCAQO embedded image coder offers improvement in subjective and objective quality for texture-rich images and experimental results show that it offers coding performance superior to or comparable to the state-of-the-art image coders.

Keywords: Embedded image coding, wavelet packet, best basis, context classification, quadtree ordering

1. INTRODUCTION

Embedded image coding has received great attention recently. In addition to providing some forms of scalability, such as quality scalability or resolution scalability, the embedded image coder has the property that the bit-stream can be truncated at any point and still decode a reasonably good image. There are three stages in the framework of embedded wavelet image coding.[1] The first stage is transformation and quantization, the second stage is modeling and ordering, and the third stage is entropy coding. Although linear correlation between wavelet coefficients is assumed negligible, nonlinear correlation is still possible and evidence shows that modeling and ordering play an important role in exploiting the nonlinear redundancy. It's widely believed that the neighboring coefficients capture essential context information, such as edges and patterns, and this information can help to achieve good compression. Many image coders[1–4] take this approach in the adaptive entropy coder, including JPEG2000. Recently, an approach called a Tarp filter has been proposed,[5] which estimates the significance probability through an IIR filtering technique on the bitplanes of the wavelet coefficients and then the estimated significance probability is used to drive a non-adaptive arithmetic coder to compress the information. Even though providing a good performance when used in a non-embedded manner, the Tarp-filter-based image coding system performs less competitively when used in an embedded manner because the Tarp filter is designed to follow the raster scan encoding order.

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Fernando Pereira, Heung-Yeung Shum, Andrew G. Tescher, Proc. of SPIE Vol. 5960
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In this paper, we concentrate on the second stage, modeling and ordering stage, and propose an embedded image coding system based on context classification and quadtree ordering in wavelet packet domain (CCAQO). Since subband correlation is mainly captured by significance coding, our focus is on significance coding. The algorithm categorizes the wavelet coefficients with the same or similar significance probability, which is estimated through the proposed FIR filtering technique on the significance states of neighboring coefficients, into several contexts using a context classifier based on Lloyd-Max algorithm. Then, the significance state of wavelet coefficient is encoded using adaptive arithmetic coder based on the classified context. In addition, combined with the structure of the best wavelet packet basis, a complete quadtree representation of wavelet packet coefficients is established to explore the ordering procedure of embedded image coding.

The paper is organized as follows. In Section 2, we present a new cost function for the best basis selection which is adopted in DWPT. Section 3 discusses the context classification and quadtree ordering scheme. The proposed embedded image coding algorithm is described in Section 4. Experimental results are presented in Section 5. Section 6 gives our conclusions.

2. BEST WAVELET PACKET BASIS SELECTION ALGORITHM

Although wavelet transform provides a very efficient representation for a broad class of natural signals, it still remains a ”fixed” decomposition that fails to fully exploit all of the source redundancy present. Wavelet packet transform is more general than wavelet transform. The non-dyadic nature of the wavelet packet transform allows us to find the best wavelet packet basis adapted to the contents of given signal and to the purpose of representation. Empirical evidence and experimental results show that using wavelet packet transform on an image can improve the PSNR significantly for some images, such as Barbara, when compared the standard wavelet transform. In addition, zerotree structure is widely used in wavelet based image coding algorithms, but it’s not suitable for highly scalable image coding, such as resolution scalability. Quadtree structure is very suitable for highly scalable image coding, and quality scalability and resolution scalability can easily be obtained by quadtree structure. The best basis structure of wavelet packet can help us to construct a complete quadtree representation of wavelet packet coefficients, since the best basis itself is also represented by quadtree structure.

A best basis that adapts well to the input signal is chosen by the cost function. Coifman et al.[6] used entropy as a cost function for best basis selection. However, since the entropy defined by Coifman et al.[6] has no connection with the classical Shannon entropy, the best basis selection based on this entropy is not always suited to image coding. Ramchandran, et al.[7] selected the best basis using the rate-distortion optimization technique. However, this approach is computational intensive involving three layers of nonlinear approximations. In addition, these best basis selection methods are all done prior to the embedded image coder, thus, they may be not always efficient for image coding.

In this paper, a new cost function for the best basis selection is proposed to match up well with the quadtree-based embedded coder. To do so, the selection procedure of the best basis is accompanied with the built-up procedure of quadtree representations of wavelet packet coefficients using the greedy growth tree algorithm. The greedy growth tree algorithm starts from a dyadic wavelet decomposition and then further decomposes each subband if that is decided to be more profitable using a cost function as a criterion. The cost function is defined by:

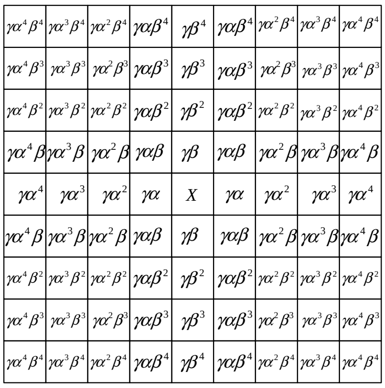
$$C(x) = \sum_{l=0}^{D_k} \sum_{i=0}^{M_l} \sum_{j=0}^{N_l} log_2 |q_k[l](i,j)| \tag{1}$$

where D_k is the quadtree depth for subband k, $q_k[l](i,j)$ denote the pre-quantized node of the quadtree level l of subband k , and $M_l \times N_l$ is the size of the quadtree level l.

3. CONTEXT CLASSIFICATION AND QUADTREE ORDERING

3.1. Significance Probability Estimation

Given a threshold T, a wavelet coefficient c is called significant if $|c| \geq T$ or insignificant if $|c| < T$. And the significance state of a wavelet coefficient c with respect to a given threshold T is denoted by $v_T(c)$, where $v_T(c) = 1$, for $|c| \geq T$,



$\gamma\alpha^4\beta^4$	$\gamma\alpha^3\beta^4$	$\gamma\alpha^2\beta^4$	$\gamma\alpha\beta^4$	$\gamma\beta^4$	$\gamma\alpha\beta^4$	$\gamma\alpha^2\beta^4$	$\gamma\alpha^3\beta^4$	$\gamma\alpha^4\beta^4$
$\gamma\alpha^4\beta^3$	$\gamma\alpha^3\beta^3$	$\gamma\alpha^2\beta^3$	$\gamma\alpha\beta^3$	$\gamma\beta^3$	$\gamma\alpha\beta^3$	$\gamma\alpha^2\beta^3$	$\gamma\alpha^3\beta^3$	$\gamma\alpha^4\beta^3$
$\gamma\alpha^4\beta^2$	$\gamma\alpha^3\beta^2$	$\gamma\alpha^2\beta^2$	$\gamma\alpha\beta^2$	$\gamma\beta^2$	$\gamma\alpha\beta^2$	$\gamma\alpha^2\beta^2$	$\gamma\alpha^3\beta^2$	$\gamma\alpha^4\beta^2$
$\gamma\alpha^4\beta$	$\gamma\alpha^3\beta$	$\gamma\alpha^2\beta$	$\gamma\alpha\beta$	$\gamma\beta$	$\gamma\alpha\beta$	$\gamma\alpha^2\beta$	$\gamma\alpha^3\beta$	$\gamma\alpha^4\beta$
$\gamma\alpha^4$	$\gamma\alpha^3$	$\gamma\alpha^2$	$\gamma\alpha$	X	$\gamma\alpha$	$\gamma\alpha^2$	$\gamma\alpha^3$	$\gamma\alpha^4$
$\gamma\alpha^4\beta$	$\gamma\alpha^3\beta$	$\gamma\alpha^2\beta$	$\gamma\alpha\beta$	$\gamma\beta$	$\gamma\alpha\beta$	$\gamma\alpha^2\beta$	$\gamma\alpha^3\beta$	$\gamma\alpha^4\beta$
$\gamma\alpha^4\beta^2$	$\gamma\alpha^3\beta^2$	$\gamma\alpha^2\beta^2$	$\gamma\alpha\beta^2$	$\gamma\beta^2$	$\gamma\alpha\beta^2$	$\gamma\alpha^2\beta^2$	$\gamma\alpha^3\beta^2$	$\gamma\alpha^4\beta^2$
$\gamma\alpha^4\beta^3$	$\gamma\alpha^3\beta^3$	$\gamma\alpha^2\beta^3$	$\gamma\alpha\beta^3$	$\gamma\beta^3$	$\gamma\alpha\beta^3$	$\gamma\alpha^2\beta^3$	$\gamma\alpha^3\beta^3$	$\gamma\alpha^4\beta^3$
$\gamma\alpha^4\beta^4$	$\gamma\alpha^3\beta^4$	$\gamma\alpha^2\beta^4$	$\gamma\alpha\beta^4$	$\gamma\beta^4$	$\gamma\alpha\beta^4$	$\gamma\alpha^2\beta^4$	$\gamma\alpha^3\beta^4$	$\gamma\alpha^4\beta^4$

Figure 1. An example of 9×9 filter matrix kernel for LH subbands

and $v_T(c) = 0$, otherwise. We define the significance probability as the probability of a coefficient c to be significant with respect to the given threshold T. The unconditional significance probability for a coefficient c is denoted by $P\{v_T(c) = 1\}$. However, the unconditional significance probability $P\{v_T(c) = 1\}$ is not enough to capture the correlation between the wavelet coefficients. Hence, in order to further capture the correlation between the wavelet coefficients, the high-order conditional significance probability for a coefficient c is introduced, denoted by $P\{v_T(c) = 1|NC\}$. NC denotes the neighborhood of c, excluding c.

Empirical evidence and experimental results show that the probability of the coefficient being significant decrease gradually from near neighbors to far neighbors for significant coefficients, and we assume that the decrease trend is proportional to an exponential decay of the distance of the current coefficient to the other ones. Assuming that the neighboring coefficients at locations $(x_k, y_k), k = 1..K$, are known to be significant with respect to T, the significance probability density of the current coefficient at location (x, y) can be estimated by the Parzen window, which is widely used in pattern classification.[9] The similar method of probability estimation is also used in Tarp-filter-based image coder,[5] but is developed independently. The significance probability estimation using the Parzen window is performed as follows:

$$p(x, y) = \sum_{k=1}^{K} \varphi(x - x_k, y - y_k) \tag{2}$$

where $\varphi(x, y)$ is a Parzen window function. The significance probability density estimation of Eq.(2) can also be considered as the convolution of the window function φ with the significance state map v which has impulses situated at $(x_k, y_k), k = 1..K$, as follows:

$$\begin{aligned} p(x, y) &= \sum_u \sum_v v_T(u, v) \cdot \varphi(x - u, y - v) \\ &= \varphi(x, y) * v_T(x, y) \end{aligned} \tag{3}$$

As is well known, the distribution of wavelet coefficient magniftudes follows the Laplacian distribution. Therefore, we can choose the Laplacian window function as the Parzen window function:

$$\varphi(x, y) = \gamma e^{-(\lambda_1|x| + \lambda_2|y|)} \tag{4}$$

where λ_1,λ_2 are the parameters which controll the decay in x, y direction, and γ is the normalized parameter which is chosen so that $\sum \varphi(x, y) = 1$.

Since the LH(vertically high-pass) subband responds most strongly to horizontal edges and HL(horizontally high-pass) subband responds most strongly to vertical edges in the original image, so we expect strong correlation amongst horizontally/vertically adjacent coefficients, respectively. Therefore, $\varphi(x, y)$ is different for LL/LH/HL/HH subbands as follows:

$$\varphi(x,y)=\begin{cases}\gamma\alpha^{|x|+|y|} & \text{for LL subbands: } e^{-\lambda_1}=e^{-\lambda_2}=\alpha\\ \gamma\alpha^{|x|}\beta^{|y|} & \text{for LH subbands: } e^{-\lambda_1}=\alpha,\ e^{-\lambda_2}=\beta\\ \gamma\beta^{|x|}\alpha^{|y|} & \text{for HL subbands: } e^{-\lambda_1}=\beta,\ e^{-\lambda_2}=\alpha\\ \gamma\beta^{|x|+|y|} & \text{for HH subbands: } e^{-\lambda_1}=e^{-\lambda_2}=\beta\end{cases} \tag{5}$$

From the assumption above, since the significance probabilities decrease as an exponential decay, one significant coefficient imposes very little impact on those very far neighbors. Therefore, we can simplify the infinite length filter to a finite length filter with a 9×9 matrix kernel. An example of 9×9 filter matrix kernel for LH subbands is shown in Figure 1. And the 9×9 filter matrix kernels for LL/HL/HH subbands are similar to those of LH subbands. This simplification makes it possible for embedded image coding, since the filtering process using the 9×9 FIR filter matrix kernel needn't follow the raster scanning order as the Tarp-filter-based image coder does, and the most significance information can be encoded and transmitted as any optimal order to achieve good rate-distortion performance. Hence, the significance probability of the current coefficient can be estimated by convoluting the corresponding 9×9 FIR filter matrix kernel with the significance states of the neighboring coefficients with respect to a given threshold, including all neighboring significant coefficients in previous threshold and in current threshold.

3.2. Context Classification

In traditional context modeling, since almost all the relevant information appears to be captured by the significance of these neighbors, the edges and patterns of neighboring coefficients are used to construct the context model. Typically, a context template is used to cover the neighbors and several distinct contexts are extracted from all possible neighborhood configurations. In EBCOT,[4] a 3×3 neighbor template is used to extract nine distinct contexts out of 256 neighbor configurations. However, the high-order conditional probability $P(v_T(c)=1|NC)$ suggests that a larger neighbor template leads to better probability estimation, so the EBCOT's 3×3 neighbor template may be too small to exploit the intra-band correlation effectively. On the other hand, a larger neighbor template also leads to more complicated contexts extraction procedure from more possible neighborhood configurations at the same time. It seems that the requirements of a larger neighbor template and a moderate context number are contradictory.

To deal with this dilemma, a context classifier, instead of a context template, is proposed to categorize the estimated significance probabilities, which are obtained by convoluting the proposed 9×9 FIR filter matrix kernel with the significance states of the neighboring coefficients, into several contexts. Even though the estimated significance probability can be used to drive a non-adaptive arithmetic coder to compress the information as the Tarp-filter-based system[5] does, we argue that this is not efficient. The main reason is that the estimated significance probability is not very accurate, rather it is just an approximate version of actual significance probability. However, the estimated significance probability provides enough information to construct the context model for adaptive arithmetic coder. In other words, the wavelet coefficients with the same or similar significance probability can be classified into the same context, and the context classification can help to achieve good compression by encoding the significance states of the coefficients using adaptive arithmetic coder based on the classified context.

The context classification procedure can also be considered as a context quantization procedure. That is say, the estimated significance probabilities can be classified into the same group using optimal quantization procedure. Since the high-order conditional probability has been converted to one-order significance probability using the proposed FIR filter, we can use the optimal scalar quantizer, instead of optimal vector quantizer, to classify the estimated significance probabilities into several contexts.

From the quantization optimization theory, if two conditions (the nearest neighbor condition and the centroid condition) are satisfied, the Lloyd-Max algorithm can be used to find optimal quantizers. Since the probability distribution function of the estimated significance probabilities to be classified is unknown, the quantizer can be designed based on a training set containing representative samples. The procedure for computing optimal scalar quantizer using Lloyd-Max algorithm is summarized as follows:
1) Training the probability distributions function $f(p)$ of the estimated significance probability p with a sufficiently large set of images so that good estimation to $f(p)$ is obtained.

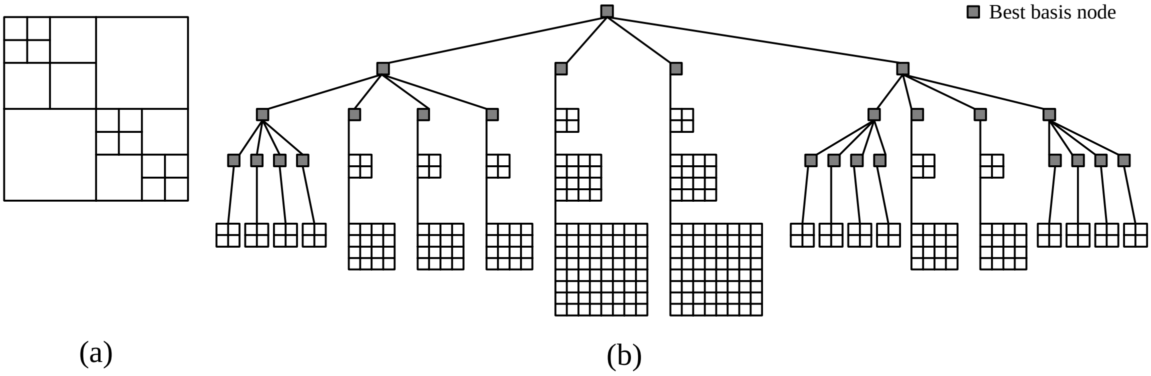


Figure 2. (a) Quadtree structure of wavelet packet decomposition, (b) Complete quadtree representation of wavelet packet coefficients

2) Starting with an initial value of q_0 and with $p_0 = 0$, successive values of p_k and q_k are calculated by recursive use of Eq. (6):

$$\begin{aligned} p_{k+1,opt} &= \frac{1}{2}(q_{k+1,opt} + q_{k,opt}); k = 1, 2, ..L \\ q_{k,opt} &= \frac{\int_{p_{k,opt}}^{p_{k+1,opt}} pf(p)dp}{\int_{p_{k,opt}}^{p_{k+1,opt}} f(p)dp}; \;\; k = 1, 2, ..L \end{aligned} \tag{6}$$

3) If, for a fixed number of quantisation levels L, q_L is the centroid between p_L and 1, then the initial choice of q_0 is correct. Otherwise the step 2 is repeated with a new value of q_0 until a certain error tolerance is achieved.

When the optimal quantizer is found using the Lloyd-Max algorithm based on the training set, the estimated significance probabilities will be quantized into several groups using the optimal quantizer and a context label is assigned to each group.

3.3. Quadtree Ordering

Embedded image coding involves the problem of ordering information according to its significance, it is preferable to encode and transmit the most significant information as early as possible. In wavelet-based image coding algorithms, the zerotree and zeroblock structure is widely used, such as SPIHT,[12] SPECK,[13] EBCOT.[4] The zerotrees and zeroblocks in these schemes implement, either implicitly or explicitly, the ordering procedure of embedded coding using quadtree structure. Combined with the structure of the best wavelet packet basis, a complete quadtree representation of wavelet packet coefficients is established to explore the ordering procedure of embedded coding in our proposed method.

The best wavelet packet basis itself is represented by quadtree structure, as shown in Figure 2(a). In addition, it is important to realize that the wavelet coefficients exhibit the characteristic of energy clustering, which means in high frequency subband the coefficients have significant amplitudes mainly along the boundaries and quadtree structure is suitable for this characteristic. So we can make use of those characteristic and establish a complete quadtree representation of wavelet packet coefficients, as shown in Figure 2(b). The quadtree representation of wavelet packet coefficients is built from top to bottom: The root node at the top quadtree level corresponds to the maximum amplitude of the all wavelet packet coefficients of all subbands; the quadtree node at the higher level is set to the maximum amplitude of the four corresponding descendent nodes at the lower level and apply them recursively to the four descendent nodes until the bottom level is reached; the bottom level of the quadtree consists of the subband coefficients. A similar quadtree splitting scheme also appears in EBCOT and SPECK; however, those quadtree schemes only represent coefficients in one block (EBCOT) or in one subband (SPECK). In the proposed method, the structure of the best wavelet packet basis helps us to connect all the separate quadtrees of each subband to form a complete quadtree representation of wavelet packet coefficients, as shown in Figure 2(b).

Figure 3. Block diagram of the CCAQO embedded image coding algorithm

To optimize the rate-distortion performance and obtain the highly scalable coding, bit-plane by bit-plane coding based on quadtree ordering is adopted. Since the quadtree representation offers an elegant way to effectively trace down to the location of significant coefficients and at the same time maximize grouping of insignificant coefficients, quality scalability and resolution scalability are both easily obtained by different quadtree ordering.

For quality scalable coding, we start the ordering and coding process from the top root node in the quadtree. If the parent node at the higher level fulfills the significant test with respect to a given threshold T, then apply recursively the process to the four descendent nodes at the lower level until the bottom level is reached. Otherwise, the quad-splitting procedure stops and the current parent node and its all offspring nodes are referred as insignificant with respect to a given threshold T.

For resolution scalable coding, we start the ordering and coding process from the leftmost leaf node of the best basis. Only when the ordering and coding process of all nodes below the previous leaf node of the best basis is finished, the process of the next leaf node of the best basis can begin.

4. EMBEDDED CODING ALGORITHM

The proposed embedded image coding algorithm based on context classification and quadtree ordering (CCAQO) is shown in Figure 3. The image is first decomposed by DWPT, and the wavelet coefficients are pre-quantized in quantization stage. Then, the quantized coefficients are encoded by the embedded bitplane coder based on context classification and quadtree ordering to generate the final bitstream. In the following sections, we present the complete description of the proposed algorithm.

4.1. Transform and Quantization

Daubechies 9/7 biorthogonal wavelet filter was employed for the DWPT. Greedy growth tree algorithm is used to find the best basis based on a new cost function which is defined in Eq. (1), and the selection procedure of the best basis is accompanied with the built-up procedure of quadtree representations of wavelet packet coefficients from top to bottom. The best basis structure is outputted as header information.

After DWPT, the wavelet coefficients are quantized with a uniform scalar quantizer with a dead zone twice the step size, which can be formulated as $c_k = \chi_k \lfloor |w_k|/\Delta_k \rfloor$, where w_k is the transform coefficient; Δ_k is the quantization step size; χ_k is the sign of quantized coefficient; c_k is the quantized coefficient. Unlike the traditional image coding system, the coding quality is not controlled by the quantization step size Δ_k. The functionality of the quantizer is just to convert the transform coefficients into integer. Instead, the effective quantizer step size is eventually controlled by the bit plane level of the final bit plane pass. The eventually effective quantization step size, δ_k, is jointly determined by the pre-quantizer Δ_k and the bit plane level of the final bit plane pass n, given by $\delta_k = 2^n \cdot \Delta_k$.

4.2. Context Classification and Quadtree Ordering

In the context classification and quadtree ordering stage, the quantized coefficients are processed through bit-plane by bit-plane with respect to a threshold set. The initial threshold is set to $T_{max} = 2^n$ where $2T_{max}$ is larger than the magnitude of maximum coefficients. Then the dimidiate decreasing threshold set (T_{max}, $T_{max}/2$,...) is used and the bit-plane coding processing is repeated until the target bit budget is achieved.

Quality scalability and resolution scalability are both easily obtained by different quadtree ordering. For quality scalable coding, we start the ordering and coding process from the top root node in the quadtree, and apply them recursively to the four descendent nodes until the bottom level is reached. For resolution scalable coding, we start the ordering and coding process from the leftmost leaf node of the best basis, and only if finishing the process of all nodes and coefficients below the previous leaf node of the best basis, then begin the process of the next leaf node of the best basis.

There are three kinds of information of the coefficients need to be encoded which are encountered during the quadtree ordering stage: the significance state, the sign bit and the refinement bit. Since subband correlation is mainly captured by significance coding, our focus is on significance coding. And the sign coding scheme and magnitude refinement scheme of EBCOT are employed in our algorithm. In order to encode the significance state of a node, we convolute the corresponding 9×9 filter matrix kernel, which is defined by Eq. (5), with the significance states of the neighboring nodes with respect to a given threshold, including all the neighboring significant nodes in the previous threshold and in the current threshold, to estimate the significance probability of the current node. After obtaining the estimated significance probabilities, we can use the optimal scalar quantizer which is given by Lloyd-Max algorithm based on the training set to classify the estimated significance probabilities into several contexts.

4.3. Entropy Coding

The entropy coder used in our embedded image coding system is context-based adaptive arithmetic coder. The significance state of each node with respect to a given threshold is encoded using the adaptive arithmetic coder based on the classified context. There are nine contexts for significance coding. And each sign bit and refinement bit is encoded based on its corresponding context. The five contexts for sign coding and three contexts for magnitude refinement are defined in EBCOT.[4]

5. EXPERIMENTAL RESULTS

For the proposed embedded image coder, we use $\alpha = 0.25$, $\beta = 0.2$ for all experiments. Although optimal α, β could be selected experimentally for each image object, we use these values as being universally good choices. The training set of images, which is used to design the optimal scalar quantizer for context classification, is a set of natural images (10 images). Even though the training set is small, the CCAQO algorithm still achieves good coding performance.

The performance of the proposed CCAQO algorithm is evaluated through extensive coding experiments. The test images are *Lena*, *Barbara*, and *Goldhill*, which are not in the training set. The proposed CCAQO algorithm was compared with the efficient zero-tree or zero-block coders, EZBC,[2] EBCOT,[4] SPIHT,[12] SPECK[13] and with Tarp-filter-based[5] image coder. In order to compare the performance of image coding with those state-of-the-art image coding algorithms, the QccPack[14] implementations of SPIHT, SPECK and Tarp-filter-based image coder are used. EBCOT is the core compression algorithm in the JPEG 2000 international standard. EZBC is an embedded image coding algorithm using zeroblocks of subband/wavelet coefficients and context modeling. The Daubechies 9/7 filters was employed for wavelet transform in all those algorithms.

The PSNR performances for popular test images *Lena*, *Barbara*, and *Goldhill* at the bitrates of 0.0625 bpp, 0.125 bpp, 0.25 bpp, 0.5 bpp and 1.0 bpp, respectively, are shown in Tables 1-3. Experimental results show that the proposed embedded image coder also offers coding performance superior to or comparable to the state-of-art embedded image coders in PSNR performance. Table 4 further summarizes the objective comparison results in form of average PSNR differences. Comparing the results by Tarp and CCAQO, we can see that the differences in PSNR performance between the two are mostly significant, for instance, more than 1 dB at the bitrates of above 0.25 bpp. It is an indication that our embedding image coder which adopts adaptive arithmetic coder based on the classified context achieves much better performance than the Tarp-filter-based system which adopts non-adaptive arithmetic coder using the estimated significance probability directly. Due to the optimal context classifier and the flexible quadtree representation ability of wavelet packet coefficients, CCAQO also outperforms the competing zero-tree or zero-block coders in the most test cases.

In Figure 4 and Figure 5, we present the subjective visual comparison of the reconstructed images: *Barbara* at the bitrate 0.125 bpp and *Goldhill* at the bitrate 0.25 bpp, respectively, using SPIHT, Tarp and CCAQO algorithms, and only 200×200 regions from the 512×512 test images are shown in those figures. As is observed, our proposed CCAQO algorithm preserves the texture details well, whereas SPIHT and Tarp algorithms fail to represent the texture details.

Table 1. PSNR evalutation for *Lena* (512x512), in dB

BitRate	0.0625	0.125	0.25	0.5	1.0
EBCOT	28.10	31.05	34.16	37.29	40.48
SPIHT	**28.38**	31.10	34.11	37.21	40.41
SPECK	28.16	30.96	34.03	37.10	40.25
EZBC	-	-	34.35	**37.47**	40.25
Tarp	28.03	30.69	33.64	36.74	39.85
CCAQO	28.31	**31.22**	**34.36**	37.41	**40.57**

Table 2. PSNR evalutation for *Barbara* (512x512), in dB

BitRate	0.0625	0.125	0.25	0.5	1.0
EBCOT	23.34	25.37	28.40	32.29	37.11
SPIHT	23.35	24.86	27.58	31.40	36.41
SPECK	23.36	24.93	27.76	31.54	36.49
EZBC	-	-	28.25	32.15	37.28
Tarp	23.23	24.78	27.25	31.07	35.90
CCAQO	**24.14**	**26.45**	**29.35**	**33.10**	**37.70**

Table 3. PSNR evalutation for *Goldhill* (512x512), in dB

BitRate	0.0625	0.125	0.25	0.5	1.0
EBCOT	26.60	28.51	30.59	33.25	36.59
SPIHT	26.73	28.48	30.56	33.13	36.55
SPECK	26.65	28.39	30.50	33.03	36.36
EZBC	-	-	30.74	33.47	36.90
Tarp	26.57	28.29	30.41	32.97	36.16
CCAQO	**26.83**	**28.65**	**30.86**	**33.57**	**36.96**

Table 4. Average PSNR differences for *Lena*,*Barbara* and *Goldhill*

BitRate	0.0625	0.125	0.25	0.5	1.0
EBCOT	-0.41	-0.46	-0.47	-0.42	-0.35
SPIHT	-0.27	-0.63	-0.77	-0.78	-0.62
SPECK	-0.37	-0.68	-0.76	-0.80	-0.71
EZBC	-	-	-0.41	-0.33	-0.27
Tarp	-0.48	-0.85	-1.09	-1.10	-1.11
CCAQO	0.00	0.00	0.00	0.00	0.00

6. CONCLUSIONS

In this paper, we present an embedded wavelet packet image coding algorithm which is based on context classification and quadtree ordering (CCAQO). Due to the optimal context classifier and the flexible quadtree representation ability of wavelet packet coefficients, it offers improvement in subjective and objective quality for texture-rich images. Although only intra-band dependency is exploited, the proposed CCAQO embedded image coder offers coding performance superior to or comparable to the state-of-art image coders.

REFERENCES

1. D. Taubman, E. Ordentlich, M. Weinberger, G. Seroussi, I. Ueno, and F. Ono, ”Embedded block coding in JPEG2000”, in *Proceedings of Int. Conf. Image Processing*, Vol.2, pp. 33-36, 2000.
2. S.-T. Hsiang and J.W. Woods, ”Embedded image coding using zeroblocks of subband/wavelet coefficients and context modeling”, in *Proc. of IEEE Int. Symp. On Circuits and Systems*, Vol.3,pp. 662-665, May 2000.
3. S. Servetto, K. Ramchandran and M. Orchard, ”Image coding based on a morphological representation of wavelet data”, *IEEE Trans. Image Processing*, Vol.8, pp. 1161-1173, Sept. 1999.
4. D. Taubman, ”High performance scalable image compression with EBCOT”, *IEEE Trans. Image Processing*, vol.9, Issue: 7, pp. 1158-1170, July 2000.
5. P. Simard, D. Steinkraus, H.Malvar, ”On-line adaptation in image coding with a 2-D tarp filter”, *Proc. of Data Compression Conference*, pp. 23-32, April 2002.
6. R.R.Coifman and M.V.Wickerhauser, ”Entropy-based algorithms for best basis selection”, *IEEE Trans. Information Theory*, Vol.38, No.2, pp. 713-718, March 1992.

(a) (b) (c)

Figure 4. Comparison of the reconstructed images for subregion 200×200 from the 512×512 test image *Barbara* at the bitrate 0.125bpp using (a) SPIHT, PSNR=24.86dB (b) Tarp, PSNR=24.78dB (c) CCAQO, PSNR=26.45dB, respectively

(a) (b) (c)

Figure 5. Comparison of the reconstructed images for subregion 200×200 from the 512×512 test image *Goldhill* at the bitrate 0.25bpp using (a) SPIHT, PSNR=30.56dB (b) Tarp, PSNR=30.41dB (c) CCAQO, PSNR=30.86dB, respectively

7. K.Ramchandran and M.Vetterli, ”Best wavelet packet bases in a rate-distortion sense”, *IEEE Trans. Image Processing*, Vol.2, No.2, pp. 160-175, April 1994.
8. J.Liu and P.Moulin, ”Information-theoretic analysis of interscale and intrascale dependencies between image wavelet coefficients”, *IEEE Trans. Image Processing*, Vol.10, pp. 1647-1658, Nov. 2001.
9. R.O.Dude, P.E.Hart, and D.G. Stork, *Pattern Classification*, John Wiley & Sons, Inc., New York, 2nd edition, 2001.
10. S.P.Lloyd, ”Least squares quantization in PCM”, *IEEE Trans. Information Theroy*, Vol.28, pp. 129-137, Mar.1982.
11. J.M.Shapiro, ”Embedded image coding using zerotrees of wavelets coefficients”, *IEEE Trans. Signal Processing*, Vol.41, pp. 3445-3463, Dec.1993.
12. A. Said and W.A. Pearlman, ”A new, fast, and efficient image codec based on set partitioning in hierarchical trees”, *IEEE Trans. on CSVT*, vol.6 , Issue: 3, pp. 243-250, June 1996.
13. I. Islam and W. A. Pearlman, ”An embedded and efficient low-complexity hierarchical image coder”, *Proc. of SPIE on VCIP*, vol.2, pp. 294-305, 1999.
14. J. E. Fowler, ”QccPack: An Open-Source Software Library for Quantization, Compression, and Coding”, in *Applications of Digital Image Processing XXIII*, (San Diego, CA), Proc. SPIE 4115, pp. 294-301, Aug. 2000.