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Lapped Biorthogonal Transform based low complexity image compression algorithm for wireless sensor network

E.V.M. Swapana[1*], C. Vasanthanayaki[2]

[1*]Department of Electronics & Communication Engineering,
Vidya Academy of Science & Technology, Thrissur, India
[2]Department of Electronics & Communication Engineering,
Govt. College of Technology, Coimbatore, Tamil Nadu, India
[*]Corresponding Author: e-mail: swapana.e.v@vidyaacademy.ac.in.

Abstract: To achieve high compression efficiency, the image compression standards used is JPEG 2000. But the algorithm used in JPEG 2000 has high complexity, large memory requirement and not suitable for distribution implementation. The novel scheme Lapped Biorthogonal Transform (LBT) based Low Complexity Image Compression Algorithm for Wireless Sensor Network is proposed to achieve lower computational complexity and memory requirement. The key features of LBT are high energy compaction, minimize blocking effect at low bit rate, less memory and is suitable for distribution implementation. To improve image compression performance, the entropy coder used is Low complexity Zerotree Codec (ZTC). The bitrate and Peak signal to noise ratio (PSNR) shows improvement over DCT, LOT and DWT and better execution time than SPIHT. The algorithm is simulated, verified and the implementation on wireless sensor networks (WSN) is on progress for energy consumption.

Keywords: image compression, computational complexity, energy consumption, WSN

1 Introduction

Image compression is the application of data compression on digital images. The objective is to reduce redundancy of the image data in order to store or transmit data in efficient form. Image compression can be lossy or lossless. The transform based method is the most popular lossy image compression method, which mainly involved discrete cosine transform (DCT) based method and discrete wavelet transfom (DWT). DCT based method often causes the boring block effect in low bit rate. DWT overcomes this problem due to its

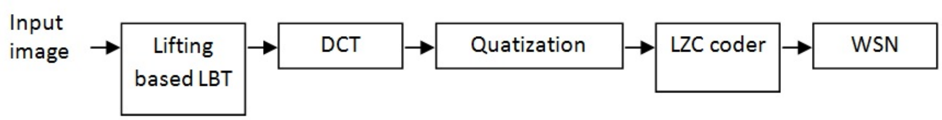

Figure 1: Basic block diagram

ability to keep trace of local features better [2]. JPEG2000 is a representative DWT based compression method, but not popular because its transform (CDF9/7) and coding process (EBCOT) are both of high computational complexity and need much more memory. To solve these problems, the Lapped Biorthogonal Transform (LBT) is proposed [7, 9].

2 Key features

In the novel scheme, LBT based Low-complexity and energy efficient image compression scheme has the following key features:

I. Instead of DCT or DWT, LBT is used for image compression. To solve the blocking artifacts, interblock spatial correlation improves the coding efficiency of the proposed algorithm when compared with DCT based methods [12]. Compared with the DWT-based ones, the proposed algorithm greatly lowers the computational complexity and reduces the required memory.

II. Golomb + Multiple Quantization (MQ) coders are used in image compression instead of arithmetic coding and the computational complexity is significantly reduced. The memory requirement is minimized.

III. A distributed implementation scheme is proposed based on a clustering architecture. It overcomes the computation and energy limitation of individual nodes by sharing the processing of tasks. This greatly prolongs the lifetime of the wireless sensor network.

The Block diagram shows the basic blocks used in the proposed scheme in Fig.1. LBT provides a factorization based on the DCT [5]. Lifting steps is provided to reduce the artifacts and distribution implementation. To improve image compression performance, the entropy coder used is Low complexity Zerotree Codec (ZTC). The specific topic/problem under discussion and the approach adopted to handle it is outlined here.

3 LBT based image compression algorithm

3.1 Lift based LBT

Lapped transform (LT) can be constructed as the pre-processing of DCT inputs in the time domain [7,9]. It eliminates or reduces the severity of coding artifacts in the reconstructed

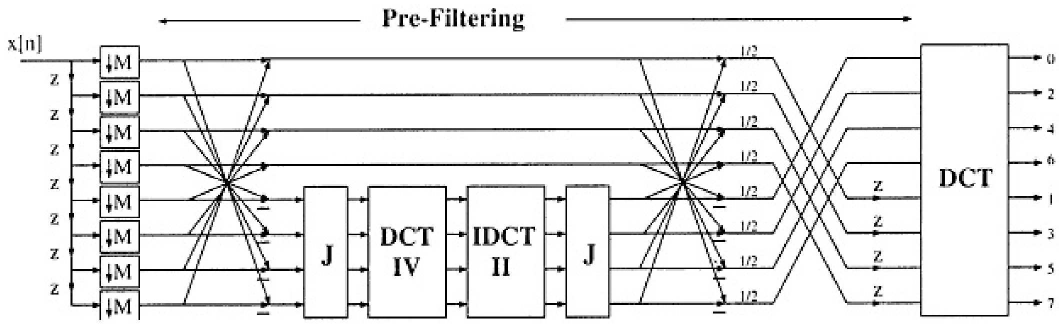

Figure 2: LOT via time domain pre-filtering

signal. LOT is represented in Figure 2.

The analysis polyphase matrix can be rewritten as

$$P_{LBT} = \begin{bmatrix} I & 0 \\ 0 & V \end{bmatrix} \begin{bmatrix} D_E - rD_O & J_{M/2}(D_E - rD_O) \\ D_E - rD_O & -J_{M/2}(D_E - rD_O) \end{bmatrix} \tag{1}$$

which is the lapped transform matrix. I is the $M \times M$ identity matrix, D_E and D_O are the even and odd base functions of DCT-II,

$$r = \text{diag}\{\sqrt{2}, 1, 1, \ldots\}$$

and J is the X counter identity matrix or reverse matrix. V is the orthogonal matrix which is approximated by $M/2 - 1$ plane rotation:

$$V = J(C^{II}_{M/2})^T C^{IV}_{M/2} J. \tag{2}$$

The type-II and type-IV discrete cosine transforms (DCT) matrices are expressed by

$$C^{II}_M = \left[a_k \cos \frac{k(2n+1)\pi}{2M} \right] \text{ where } 0 \le k, n \le M - 1 \tag{3}$$

and

$$C^{IV}_M = \left[a_k \cos \frac{(2k+1)(2n+1)\pi}{4M} \right] \text{ where } 0 \le k, n \le M - 1 \tag{4}$$

where $a_0 = \sqrt{2}/2$ and $a_k = 1$ for $1 \le k \le M - 1$. The Biorthogonal extension is done by Pre-filtering process. The matrix V controls pre-filtering. It holds all of the degrees of freedom in the structure [9, 11]. However, just to maintain FIR perfect reconstruction, V only has to be invertible. It represent alias in the singular value decomposition form:

$$V = J(C^{II}_{M/2})^T S C^{IV}_{M/2} J \tag{5}$$

where the matrix V controls pre-filtering and contains all of the degrees of freedom in the structure. S is limited to diag$\{s, 1, 1, \ldots\}$, where s is a scaling factor.

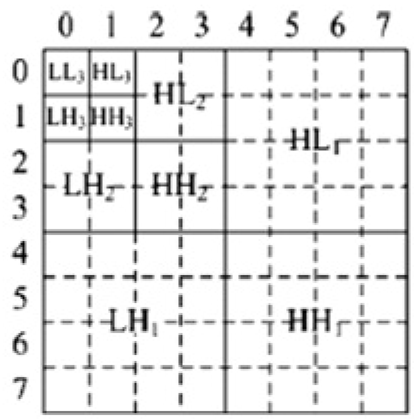

Figure 3: LBT zerotree structure

Q	**Output bits**	R	**Output bits**
0	0	0	0000
1	10	1	0001
2	110	2	0110
$\vdots$		$\vdots$	
N	......	N	......

Table 1: Encoding of quotient and remainder part for Golomb

3.2 Low-Complexity Zerotree Coding (LZC)

The distribution of quantized coefficients of LBT is similar to DWT which has a zerotree structure. The zeortree structure of 8×8 LBT is illustrated in Fig.3. The element in every pane is a quantized coefficient of LBT. The energy of the coefficients, that is, the absolute value, decreases from top left corner to bottom right. Therefore, separating the entire block into 10 sub bands by the solid lines, the LBT coefficients can be classified by the sub-band that they belong to and then coded separately [3].

3.3 Golomb codec

Golomb coding is a lossless compression. Golomb coding is used for the occurrence of small values in the input stream which is significant more likely than large values. Golomb coding uses a tunable parameter M to divide an input value into two parts: q, the result of a division by M, and r, the remainder. For simple binary coding, M is taken as power of two as shown in Table 1.

3.4 MQ codec

MQ-Coder is an entropy coder, rather than coding the binary value of the input symbol (the current bit), that encodes a binary information which indicates if the symbol being coded is Most Probable Symbol (MPS) or Less Probable Symbol(LPS). C and A refer to the base and length of the current interval, while Q_E is the estimated probability of the LPS.

If the decision value is MPS, then

$$C = C + AXQ_E \quad \text{and} \quad A = A - AXQ_E. \tag{6}$$

If the decision value is LPS, then

$$C = C \quad \text{and} \quad A = A - AXQ_E. \tag{7}$$

To avoid multiplication, approximation is done by equating $A = 1$. As Q_E becomes smaller, A reduces. Renormalization is done when A goes below 0.75. A and C are doubled. LPS becomes larger and so conditional exchange is used.

3.4.1 Pseudocode for MQ coder

MPS coding

```
A = A − Q_e
If A < min
    If A < Q_e
        A = Qe
    Else
        C = C + Q_e
    End
    R( )
Else
    C = C + Q_e
End
```

LPS coding

```
A = A − Qe
If A < Q_e
    C = C + Q_e
Else
    A = Q_e
End
R( )
```

MPS renormalisation

```
I = Index(CX)
I = NMPS(I)
Index(CX) = I
Q_e(CX) = Q_{e_value}(I)
```

LPS renormalisation

```
I = Index(CX)
If Switch(I) = 1
    MPS(CX) = 1 − MPS(CX)
End /* ( 1 → 0 or 0 → 1) */
I = NLPS(I)
Index(CX) = I
Q_e(CX) = Q_{e_value}(I)
```

3.5 Zerotree codec

For better compression, an adaptive arithmetic coder is used to encode the binary symbols [8]. The main objective is to code initially dc coefficients precisely, and then the low to high-frequency ac coefficients. ZTC is used to reduce the number of bits required to represent these zerotrees. All zerotrees are extracted and coded by ZTC. The coefficient scanning, tree growing, and coding are done in one pass.

3.6 Algorithm

X is denoted as the quantized 8×8 blocks of coefficients and $X(i,j)$, $i,j = 0,\ldots,7$ are the quantized coefficients. $C(X(i,j))$ are the children of $X(i,j)$ and $D(X(i,j))$ are descendants of $X(i,j)$ other than $C(X(i,j))$. Steps of coding are given below:

1. Code $X(0,0)$ is taken by Golomb and MQ codec.
2. Code $x = X(0,0)$ with zerotree coding.
   - 2.1 If x has no children, end coding.
   - 2.2 Else if all the children of x is zero,output 0; Otherwise go to Step 2.3.
   - 2.3 2.3. Output becomes 1, and code every children of x by Golomb and MQ codec.
     - 2.3.1 Conditions applied are : If all the coefficients in $D(x)$ are 0, output 0; otherwise go to Step 2.3.2.
     - 2.3.2 Output becomes 1, and code the coefficients in $C(x)$ with zerotree codec separately.

All quantization steps are completed before the zerotree coding and no list is needed. The distribution of quantized coefficients of LBT is similar to DWTs. Practically, the signal put into the Golomb codec does not follow a geometric distribution well. Therefore, an MQ codec is placed after the Golomb codec for further coding.

4 System model

The energy consumed in transmission per bit is

$$E_{TX} = E_{\text{elec}} + E_{\text{fs}}^2, \qquad d > d_0 \tag{8}$$
$$E_{TX} = E_{\text{elec}} + E_{\text{mp}}^2, \qquad d \leq d_0 \tag{9}$$

The energy consumed in reception per bit is $E_{\text{RX}} = E_{\text{elec}}$ where E_{elec} is the energy consumed by the circuit per bit, d is the distance between the wireless transmitter and the receiver, and E_{fs} or E_{mp} is the amplifier energy that depends on the transmitter amplifier model. The energy consumed in image compression per bit is

$$E_{\text{cp}} = 2\left(E_{\text{pre}} + E_{\text{DCT}}\right) + E_{\text{code}} \tag{10}$$

where E_{pre} is the energy dissipated for one-dimensional binary LBT pre-processing. E_{DCT} is the energy dissipated for one dimensional binary DCT. E_{code} is the energy spent in coding [4, 10].

5 Network Structure

As each sensor node is power-constrained, the lifetime of WSNs is limited [1]. Efficiently organizing sensor nodes into clusters is useful in reducing energy consumption. Cluster heads can serve as fusion points for the aggregation of data, so that the amount of data that is actually transmitted to the base station is reduced. By using LEACH, all the nodes commonly run in a single hop homogeneous network. The cluster-head role is rotated randomly and periodically distributing the energy consumption evenly among all sensors in the network. The camera nodes should adjust their transmit power to communicate with the cluster head [4].

6 Application

This implementation is done on wireless sensor network. During the transmission of the image through the nodes in wireless sensor network [6], the energy consumption using various methods is considered. Research is in progress to obtain energy calculation.

7 Simulation result

Table 2 gives the PSNR of different methods. Table 3 shows comparison with compression ratio and PSNR of LBT and Table 4 gives the execution time taken in executing time for SPIHT and LBT based algorithm. Simulation results are compared with DCT, LOT and DWT. Results show that proposed work lapped biorthogonal transform has better PSNR when compared to DCT, DWT and LOT and faster execution time when compared to SPIHT at low bitrate.

Sl. No.	**Bpp**	**PSNR**			
		DCT	LOT	DWT	LBT
1.	1	6.8352	16.3805	18.2458	18.7561
2.	0.75	5.0945	14.9891	15.7451	17.2547
3.	0.5	4.4334	14.1254	16.5847	16.6737
4	0.25	2.5849	10.7779	12.8963	13.3822

Table 2: PSNR of different methods

Compression ratio	PSNR
8 :1	18.7561
16:1	16.6737
32:1	12.2107

Table 3: Comparison with compression ratio and PSNR of LBT

Bitrate	1.00	0.5	0.25
SPIHT	0.41	0.42	0.37
LBT based	0.41	0.36	0.33

Table 4: Time spent for different methods

8 Conclusion

The binary LBT based compression method gets higher PSNR and better image quality than binary DWT based one, and is similar to SPIHT, however, spends less time that SPIHT needs and much less memory. Our method is competitive, especially for real time processing and small devices.

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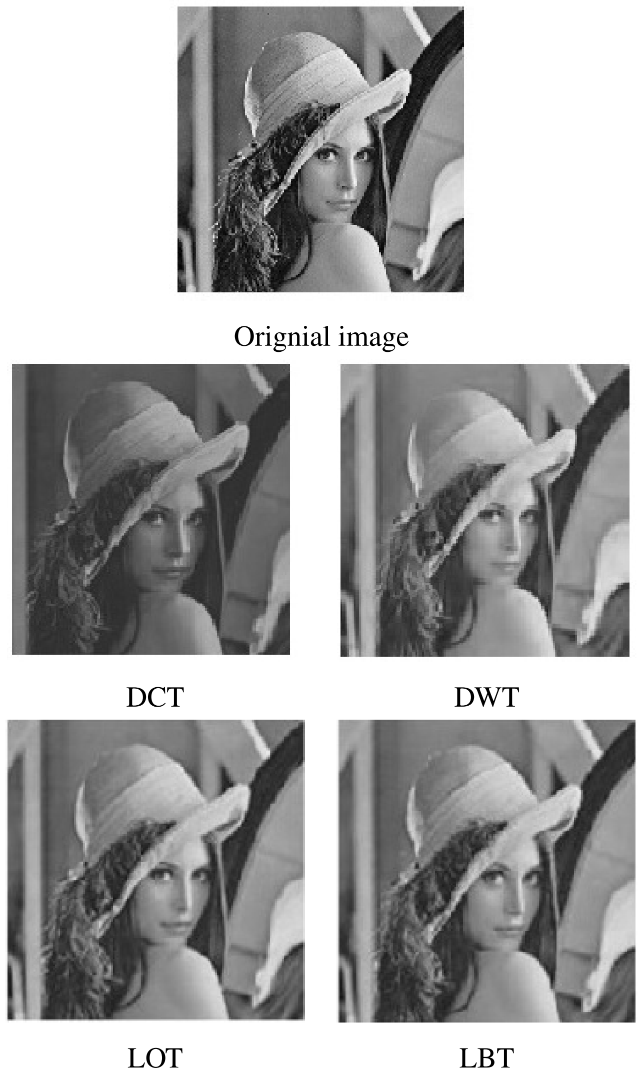

Figure 4: Input Lena image and reconstructed images with size 512×512

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