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Performance Evaluation of Wavelet based Image Compression Techniques for Wireless Multimedia Sensor Networks

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Abstract— ***The availability of advanced low cost hardware devices such as micro-electro-mechanical system (MEMS) based camera sensors technology, low power analog and digital electronics, and low power radio frequency (RF) integrated circuits design has led to the development of wireless multimedia sensor networks (WMSNs) to communicate multimedia information such as audio, video and still images from the environment for a wide range of applications like video surveillance, automated assistance for elderly, environmental monitoring, industrial process control, and advanced health care delivery. Sensor nodes in wireless sensor networks have very limited resources such as low memory capacity, low processing capability, and low data rate or limited wireless channel bandwidth. Energy consumption is also one of the critical problems which affect the lifetime of wireless sensor networks as the sensor nodes are battery operated. Image compression is one of the techniques to reduce the energy consumption of such sensor nodes to increase the life time of sensor networks. In this paper, we have evaluated performance parameters of image compression like PSNR, CR, processing time, and memory consumption using three image coding techniques (EZW, SPIHT, and SPECK) and lifting-based discrete wavelet transform (CDF 9/7). The experimental results show the overall performance of SPIHT algorithm is better than the other compression techniques for low bit rates < 1 bpp.***

Keywords— ***WMSN, Image compression, EZW, SPIHT, SPECK***

I. INTRODUCTION

Wireless multimedia sensor network (WMSN) is composed of low cost small camera sensor nodes that are capable of acquiring multimedia contents such as image data from the environment which is source node, processing it, and then sending that processed data to a base station or sink node using wireless channel. Wireless multimedia sensor networks (WMSNs) have a wide range of real-world applications like in video surveillance, home automation systems, automated assistance for elderly, environmental monitoring, industrial process control, and advanced health care delivery. But the nature of the size of image data is too large to be processed by sensor nodes in WMSN which have low memory capacity, low processing speed, and low data rate or limited wireless channel bandwidth [1] (Fig. 1). Energy consumption is also one of the main challenges which affect the lifetime of wireless sensor networks as the sensor nodes in WSNs get power from very low voltage batteries and they are deployed in the order of hundreds to thousands of nodes, which makes replacing and recharging the batteries infeasible in practice.

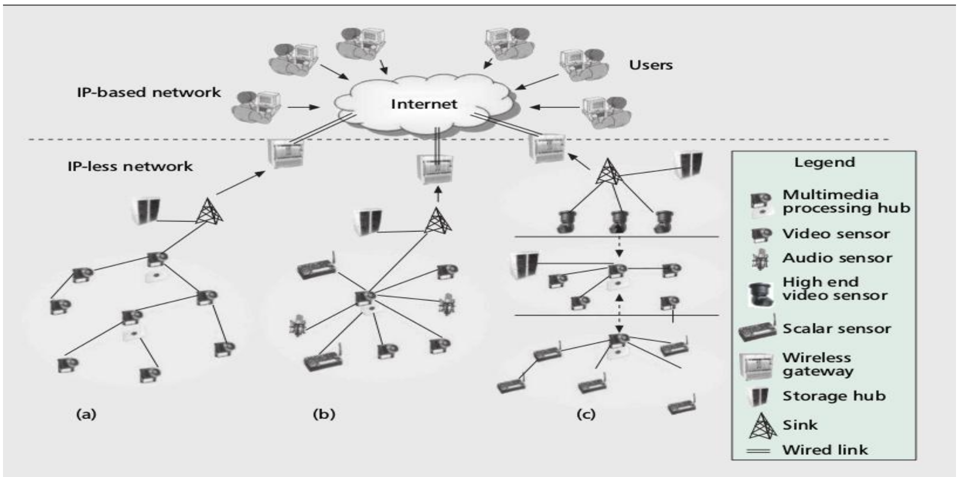


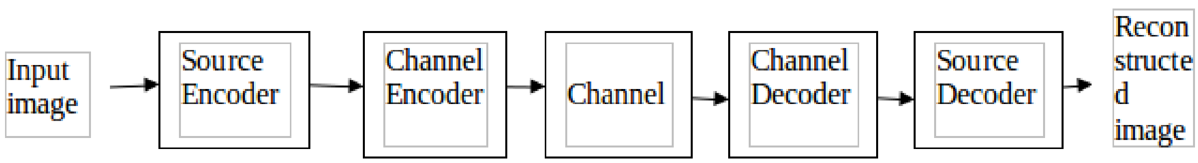
Fig. 1: Wireless Multimedia Sensor Network Architecture [1]

Image compression is a technique to reduce the amount of data required to represent a digital image by removing redundant data observed. Three basic redundancies can be exploited in digital image: inter-pixel or spatial redundancy, psycho- visual redundancy and coding redundancy [2]. In order to reduce the redundancies, many image compression techniques have been proposed and performed.

Discrete cosine transform (DCT) based image compression algorithms like JPEG are low complexity and low memory techniques [3]. But they have poor image quality at low bit rates because of blocking artifacts. JPEG2000, a new standard for compression of images, is based on discrete wavelet transform (DWT) which elliminates the blocking artifacts at high compression ratio [4]. DWT is most powerful due to ease of computation and its multiresolution analysis or decomposition of an image into spatial sub bands [5]. Cohen-Daubechies-Feauveau (CDF) 9/7 wavelet is the most popular biorthogonal wavelet that has been adopted by the FBI in finger print image compression [6]. JPEG2000 compression standard also uses CDF 9/7 and LeGall 5/3. Wavelet based image compression technique consists of two stages; wavelet transform computation of an image followed by coding these transformed coefficients. In the first stage, the transformedcoefficients are prepared in a way suitable for image coding. Many image coder algorithms are proposed to compress the wavelet transformed coefficients. Among these algorithms are the embedded zerotree wavelet (EZW) [7], set partitioning in hierarchical trees (SPIHT) [8], and the set partitioned embedded block coder (SPECK) [9] being the most famous ones. An important feature of these image coders is the property of embedded and progressive transmission which is required for low data rate applications in WMSN. Performance parameters of image compression techniques depend on the quality of image using PSNR, compression ratio, processing speed, and memory requirements [10]. In this paper, we used lifting based Cohen-Daubechies-Feauveau wavelet (CDF) 9/7 with encoding methods EZW, SPIHT, and SPECK. We compared the performance parameters of these image coders using grayscale Lena image of size 512X512 pixels to identify suitable compression technique for WMSN. The paper is organized as follows: Section II describes basics of image compression. Discrete wavelet transform techniques is discussed in section III in detail. Section IV describes the image coding techniques. The results, discussion, and analysis are explained in Section V. Finally, conclusion will be discussed in section VI.

II. IMAGE COMPRESSION

Image is the most important information carrying media in everyday personal life for communication. Every day large amount of information is stored, processed and transmitted digitally. Uncompressed image has large amounts of data. There is large amount of redundancies in any natural image due to high correlation of the pixels in the image which requires large amount of memory storage and transmission bandwidth [19]. Methods of compressing image prior to storage or transmission are of practical interest. Due to the limited available bandwidth in WMSN, an image captured by a sensor node needs to be processed and compressed before transmission. Many research works have pointed out that transform-based algorithms are better than non-transform- based techniques which makes suitable for the encoder to be less complex and implement on low power applications such as wireless multimedia contents, like images and videos which require more extensive bandwidth for communication [20]. Image coding techniques based on transform use a mathematical transform to map the image pixel values onto a set of decorrelated coefficients, thereby removing inter-pixel redundancy. These coefficients are then quantized to remove psycho-visual redundancy, and encoded to improve coding efficiency. The importance of transform-based coding schemes is their excellent energy compaction property, i.e. large fraction of total energy of image is packed in few coefficients. Most of the transform coefficients for natural images have small magnitudes and can be quantized and encoded without causing significant loss of information. A typical image compression consists of two steps as can be seen in Fig. 2: a transform (like discrete wavelet transform (DWT) stage, as well as quantization and entropy coding Stages. Recent image compression techniques combine the quantization and encoding blocks into a single unit. The components of an image compression system at the sender sensor node and receiver nodes of WMSN are shown in Fig. 3 and Fig. 4 respectively.



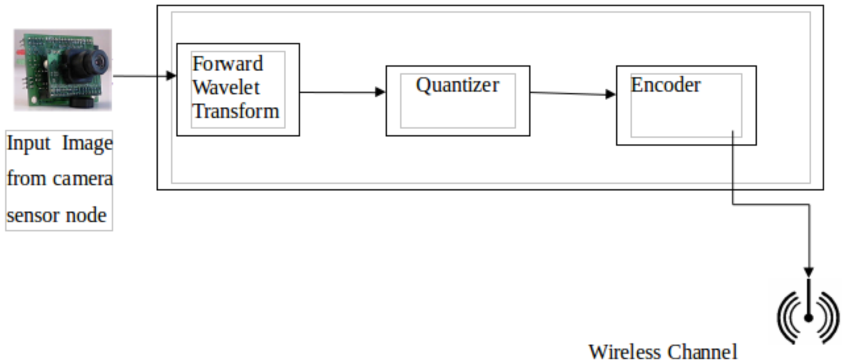
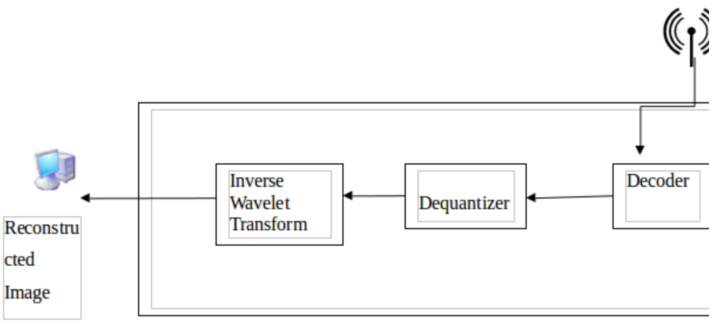


Fig. 3: Image compression at the sending node.



There are many transform techniques like discrete cosine transform (DCT) and discrete wavelet transform (DWT). For compression purposes, the higher the capability of energy compaction, the better the transform. From the experimental analysis of DCT and DWT using TelosB motes, DWTsignificantly outperforms than DCT and is more suitable for implementation in WMSN [16]. The Discrete Wavelet Transform (DWT) is most popular transform employed in image coding nowadays. The advantage of the DWT lies in ease of computation and its decomposition of an image into spatial sub bands, the conservation of energy, energy compaction, and quantization error introduced to coefficients will spread through reconstructed image with the shape of corresponding wavelet. As high compression ratio is required for low cost camera sensor networks with low bandwidth, discrete wavelet transform (DWT) based image compression is most popular transform which achieves superior image quality. Image compression techniques can be classified as lossless and lossy. Lossless method reconstructs the original image with excellent image quality. Lossy technique is highly required in WMSN because of lesser processing time, higher compression ratio and lesser energy consumption than the lossless technique. In our study, we have used lossy and wavelet based image image compression techniques (EZW, SPIHT, and SPECK) which are briefly described in sections II and III.

III.DISCRETE WAVELET TRANSFORM TECHNIQUES

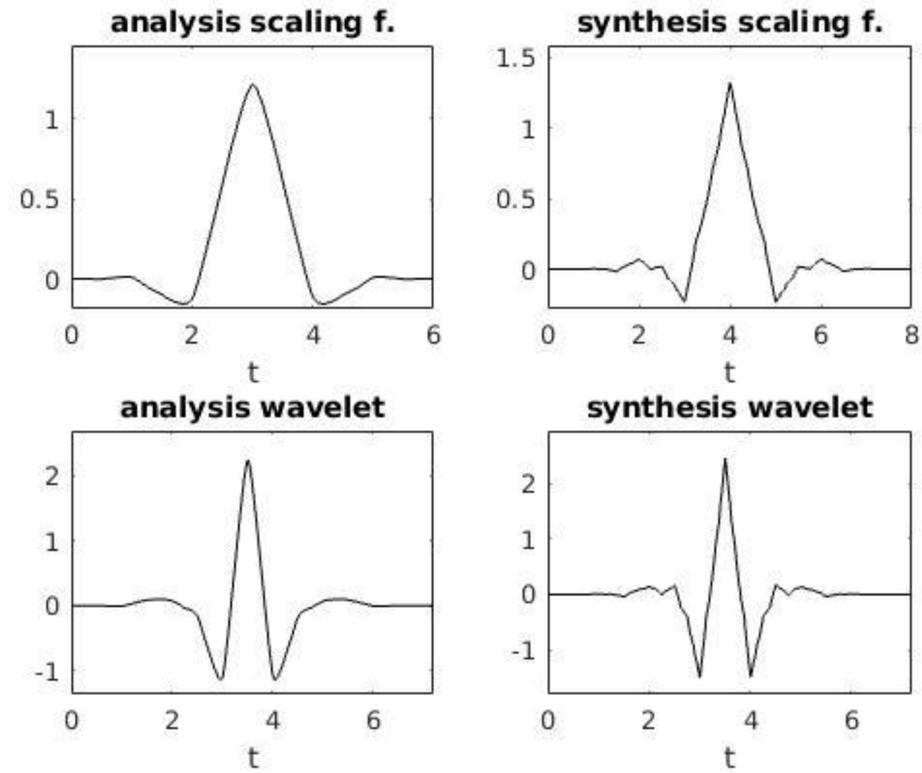
Discrete wavelet transform is a method used for the decomposition of a signal using wavelets. Many constructions of wavelets have been introduced in the literature [11]. I. Daubechies [12] constructed orthonormal bases of compactly supported wavelets. Wavelets are functions generated by dilation and translation of a single mother wavelet function ψ(t) as given in equation (1) and are used to both analyze and represent general function.

$$\psi_{a,b}(t) = a^{-1/2}\psi(\frac{t-a}{b}) \qquad (1)$$

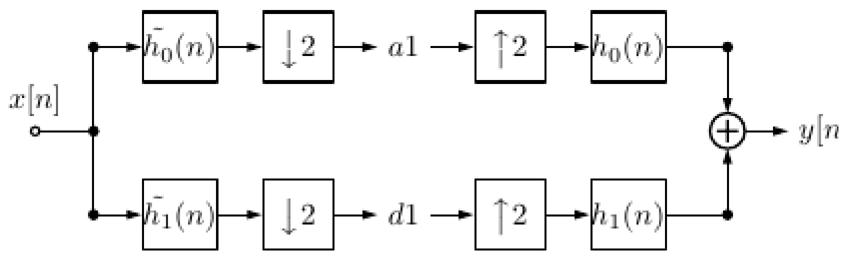
We can get discrete wavelet transform by putting $a = 2^{-j}$ and $b = k2^{-j}$ in the above equation to get equation (2).

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - k) \quad (2)$$

Cohen- Daubechies-Feauveau (CDF) [13] biorthogonal wavelets provided several families of symmetric (linear phase) biorthog- onal wavelet bases. Hasan and Ngah [18] showed that the biorthogonal Daubechies 9/7 wavelet (Cohen-Daubechies- Feveau wavelet) which contains smooth functions of relatively short compactly supported and symmetric wavelets is the most appropriate filter suitable for implementation in image compression because of their linear phase characteristics. As the biorthogonal Daubechies 9/7 wavelet [6] (also called FBI- fingerprint wavelet or Cohen-Daubechies-Feveau wavelet) is used in many wavelet compression algorithms, including the embedded zerotree wavelet (EZW) [7], the set partitioning in hierarchical trees (SPIHT) algorithm [8], and the JPEG2000 compression standard for lossy compression [3], we have used CDF 9/7 wavelet in our study. The scaling and wavelet func- tions of CDF 9/7 wavelet is shown in Fig. 5.



A
biorthogonal wavelet system consists of quadrature mirror filters referred to as h_0 (low pass filter) and h_1 (high pass filter) which are used for multi resolution sub band decomposition of a signal using wavelets as shown in Fig. 6.



In a biorthogonal wavelet families like CDF 9/7, a primal scaling function $\psi(t)$ and a dual scaling function $\tilde{\psi}(t)$ are defined by equation (3) and (4) respectively.

$$\psi(t) = \sqrt{2}\sum_{n} h_0(n)\psi(2^j t - n) \qquad (3)$$

$$\tilde{\psi}(t) = \sqrt{2}\sum_{n} \tilde{h_0}(n)\tilde{\psi}(2^j t - n) \qquad (4)$$

A primal and a dual wavelet are also defined by equation (7) and (8) respectively.

$$\phi(t) = \sqrt{2}\sum_{n} h_1(n)\psi(2^j t - n) \qquad (5)$$

$$\tilde{\phi}(t) = \sqrt{2}\sum_{n} \tilde{h_1}(n)\tilde{\psi}(2^j t - n) \qquad (6)$$

A. Conventional Discrete Convolution Method

Mallat [4] proposed the traditional method of computing discrete wavelet transform (DWT) of images. DWT is implemented using filter banks. A filter bank consists of quadrature mirror filters which are used for multi resolution sub band decomposition using wavelets. We can use convolution for the filters to compute discrete wavelet transform of an image. Filter coefficients for the low pass and high pass filters of both analysis and synthesis side of the CDF 9/7 wavelet filter is give in Table I [11].

TABLE I: Filter coefficients of the Daubechies 9/7 wavelet

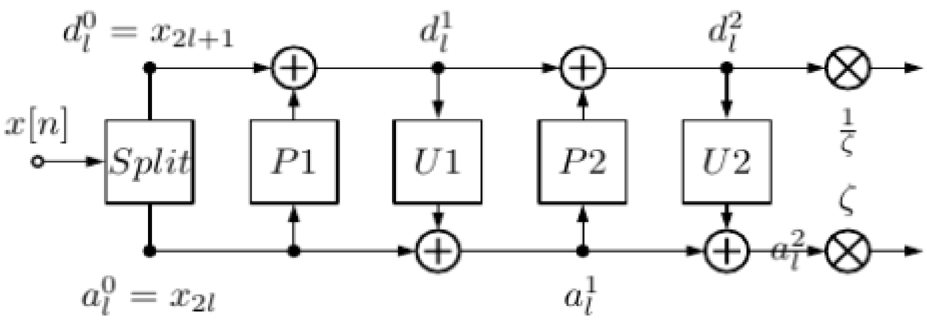
j	Analysis low pass	Analysis High pass	Synthesis low pass	Synthesis high pass
-4	0.037828			0.037828
-3	−0.023849	0.064539	−0.064539	0.023849
-2	−0.110624	−0.040689	−0.040689	−0.110624
-1	0.037828	−0.418092	0.418092	−0.377403
0	0.852699	0.788486	0.788486	0.852699
1	0.377403	−0.418092	0.418092	−0.377403
2	−0.110624	−0.040689	−0.040689	−0.110624
3	−0.023849	0.064539	−0.064539	0.023849
4	0.037828			0.037828

The traditional method of computing discrete wavelet trans- form (DWT) of images is implemented with memory intensive and time consuming algorithms and therefore has very high system resource requirements which exceed the computational and memory resources of low-complexity wireless sensor nodes.

B. Lifting Based Discrete Wavelet Transform

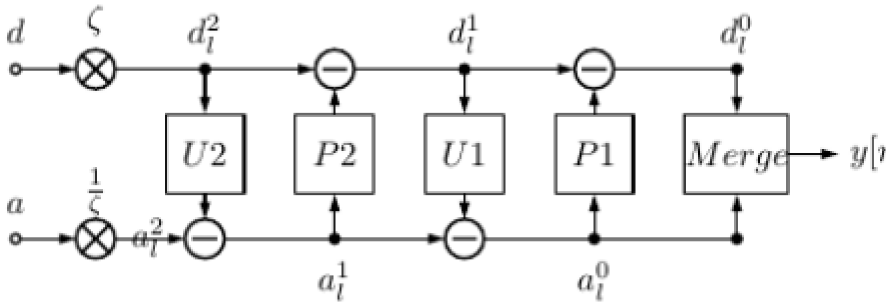
W. Sweldens [14] showed how any discrete wavelet transform can be decomposed into a sequence of simple filtering steps (lifting steps). CDF 9/7 wavelet forward lifting structure and inverse lifting structure for wavelet transform computation are shown in Fig. 7 and Fig. 8. The forward Lifting Scheme consists of three stages: Split, predict and update. The first step splits the signal data x[n] into two subsets x_e [n](even) and x_o [n](odd). The new data sequence is given by $x_e[n] = x[2n]$ and $x_o[n] = x[2n + 1]$. The second step calculates the wavelet coefficients (high pass) as the failure to predict $x_o[n]$ based on $x_e[n]$. The third step updates the $x_e[n]$ using the wavelet coefficients. Once we have the forward transform, we can derive the inverse by reversing the operations and change "+" and "-". The idea generates the inverse transform as $x_e[n] = x_e[n]- U (x_o[n])$, $x_o[n] = x_o[n]+ P (x_e[n])$, $x[n] = merge(x_e[n], x_o[n])$.

$$P(z) = \begin{bmatrix} 1 & \alpha(1+z^{-1}) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ \beta(1+z) & 1 \end{bmatrix} \begin{bmatrix} 1 & \gamma(1+z^{-1}) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ \delta(1+z) & 1 \end{bmatrix} \begin{bmatrix} \zeta & 0 \\ 0 & \frac{1}{\zeta} \end{bmatrix}$$



The parameters α, β, γ , δ, and ζ can be derived through a factoring algorithm [15] giving any FIR wavelet transform can be factored into a sequence of lifting steps. For the CDF 9/7 wavelet, the parameters and forward lifting steps are given as following:

$$\begin{aligned}
&\alpha \approx 1.586134342 \\
&\beta \approx 0.05298011854 \\
&\gamma \approx 0.8829110762 \\
&\delta \approx 0.4435068522 \\
&\zeta \approx 1.149604398 \\
&a_l^0 = x_{2l} = [x(2), x(4), x(6), ...x(2N)] \\
&d_l^0 = x_{2l+1} = [x(1), x(3), x(5), ...x(2N-1)] \\
&d_l^1 = d_l^0 + \alpha(s_l^0 + s_{l+1}^0) \\
&a_l^1 = s_l^0 + \beta(d_l^1 + d_{l-1}^1) \\
&d_l^2 = d_l^1 + \gamma(s_l^1 + s_{l+1}^1) \\
&a_l^2 = s_l^1 + \delta(d_l^2 + d_{l-1}^2) \\
&a = \zeta s_l^2 \\
&d = \frac{d_l^2}{\zeta}
\end{aligned}$$



Inverse lifting steps are given as following:

$$
\begin{aligned}
d_l^2 &= \zeta d \\
a_l^2 &= \tfrac{a}{\zeta} \\
a_l^1 &= s_l^2 - \delta(d_l^2 + d_{l-1}^2) \\
d_l^1 &= d_l^2 - \gamma(a_l^1 + a_{l+1}^1) \\
a_l^0 &= a_l^1 - \beta(d_l^1 + d_{l-1}^1) \\
d_l^0 &= d_l^1 - \alpha(a_l^0 + s_{l+1}^0) \\
y[n] &= merge(a_l^0, d_l^0)
\end{aligned}
$$

Lifting scheme can be used to speed up the fast wavelet transform for decomposition and to perform fully in-place calculation of the wavelet transform which can reduce the memory requirement. Lifting based wavelet transform is therefore suitable for discrete wavelet transform computation in wireless sensor nodes which have low memory and limited processor capability.

IV. IMAGE CODING TECHNIQUES

The embedded zerotree wavelet (EZW) [7], set partitioning in hierarchical trees (SPIHT) [8] and set partitioned embedded block coder (SPECK) [9] are wavelet based image compression techniques. SPIHT and SPECK are the most popular image coding algorithms due to their superior compression and low computational complexity to encode wavelet transformed image both algorithms use multiple linked lists to track the locations of significant/ insignificant coefficients or sets (blocks or trees).For efficient compression of images, a number of image coding algorithms have been developed.

A. EZW Algorithm

Shapiro [7] introduced an image coding technique called embedded zerotree wavelet (EZW), an effective and computationally simple technique for image compression, having the property that the bits in the bit stream are generated in order of importance yielding a fully embedded code which represents a sequence of binary decisions that distinguish an image from the null image. EZW algorithm is based on the discrete wavelet transform (DWT) or hierarchical sub band composition, prediction of the absence of significant information across scales by exploiting self similarity inherent in images, entropy coded successive approximation quantization and universal lossless data compression. EZW has laid foundation for wavelet based efficient embedded image coders. EZW algorithm performs the following steps.

Step 1. Choose initial threshold, $T_0 = 2^{(floor(log2(max(X(i,j)))))}$

Step 2. Update threshold, $T_k = T_{(k-1)/2}$

Step 3. Significance pass. Test each transform value x(k) as

if (| x(k) |≥ T_k)

output sign of x(k)

xq (m) = T_k

elseif (| x(k) |< T_k)

x_q (m) = 0

Step 4. Refinement pass. For each significant value x(k)

if (| x(k) |∈ [xq (m), xq (m) + T_k))

output bit 0

elseif (| x(k) |∈ [xq (m) + T_k , xq (m) + 2T_k)

output bit 1

x(k) = x q (m) +T_k

Step 4. Loop. Repeat steps 2 through 4

B. SPIHT Algorithm

SPIHT algorithm proposed in [8] is useful for embedded coding. It uses a partitioning of the trees in a manner that tends to keep insignificant wavelet coefficients together in larger subsets. The partitioning decisions are binary decisions to generate the bit stream at the encoder and are transmitted to the decoder. Finally, after decoding the bit stream generated at the Source encoder using SPIHT algorithm, it will be decoded the bit stream to obtain reconstructed image in wavelet domain. SPIHT algorithm proposed in [8] is useful for embedded coding. It uses a partitioning of the trees in a manner that tends to keep insignificant wavelet coefficients together in larger subsets. The partitioning decisions are binary decisions to generate the bit stream at the encoder and are transmitted to the decoder. Finally, after decoding the bit stream generated at the Source encoder using SPIHT algorithm, it will be decoded the bit stream to obtain reconstructed image in wavelet domain. SPIHT algorithm performs the following steps.

Step 1: Initialize, n = blog 2 (max(| coeff |))

LIP = All elements in tree roots

LSP = Ø

LIS= descendants of roots

Step 2: Significance Map Encoding (Sorting Pass)

Process LIP

for each coeff (i, j) in LIP

output S_n (i, j)

if S_n (i, j) = 1 then

output sign of coef f (i, j) : 0/1 = −/+

move (i, j) to the LSP

endif

endloop over LIP

Process LIS

for each set(i, j) in LIS do

if type D (set of coordinates of all descendants of node (i,j)) then

Send S_n (D(i, j))

if S_n (D(i, j)) = 1 then

for each (k, l) ∈ O(i, j)(set of coordinates of all offspring of node (i,j))

output S_n (k, l)

if S_n(k, l) = 1 then add (k, l) to the LSP and output sign of coeff

if S_n(k, l)= 0 then add (k, l) to the end of the LIP

endfor

endif

else type L (all descendents except the offspring) then

Send S_n (L(i, j))

if S_n (L(i, j)) = 1 then

add each (k, l) ∈ O(i, j) to end of LIS as type D

remove (i, j) f rom the LIS

endif

endloop over LIS

Step 3: Refinement pass

Step 4: Update n=n-1

Process LSP

for each element (i, j) in LSP except those just added above do

output the nth most significant bit of coef f

end

Step 5: Loop. Repeat steps 2 through 4.

C. SPECK Algorithm

SPECK [9] proposed by Pearlman et al., is bit plane coding algorithm, and encodes significance map of bit planes in decreasing order of their importance. SPECK coder uses two types of set: S and I set. In the process of coding, S sets are partitioned by quad partitioning scheme while I sets are partitioned by octave band partitioning scheme. Each pass of SPECK comprises of sorting, and refinement. It uses two lists: list of insignificant sets (LIS) and list of significant pixels (LSP) to store state of sets and coefficients. SPECK algorithm performs the following steps.

Step 1: Initiallize, n = log 2 (max(| coef f |))

Partition wavelet transformed image in to two sets S and I

Add S to LIS and set LSP = ∅

Step 2: Sorting Pass

in increasing order of size of sets (smaller sets first)

for each set S ∈ LIS do ProcessS(S)

```
ProcessS(S)
    output Γn (S)
    if Γn (S) = 1 then
        if S is a pixel then
            output sign of S and add S to LSP
        else CodeS(S)
    if S is ∈ LIS
        remove S from LIS
    else
    if S is not ∈ of LIS , add S to LIS

CodeS(S)
        Partition S into f our equal subsets O(S)
        for each set S i ∈ O(S)(i = 0, 1, 2, 3) do
            output Γn (Si )
            if Γn (Si ) = 1
                if S i is a pixel,
                    output its sign and add S i to LSP
                else
                    CodeS(Si )
            else
                add S i to LIS
if I ! =0, then ProcessI()

ProcessI()
    output Γn (I)
    if Γn (I) = 1 then CodeI()

CodeI()
    Partition I into four sets - three Si and one I
        for each of the three sets S i (i = 0, 1, 2)
            ProcessS(S i )
    ProcessI()
```

Step 3: Refinement pass. For each (i,j) ∈ LSP, except those included in the last sorting pass, output the nth MSB of | C (i,j) |.

Step 4: Threshold update n=n-1, go to step 2

V. RESULTS AND DISCUSSION

In this section, we discussed the results of EZW, SPIHT, and SPECK image compression techniques. We first defined the perfor- mance parameters and then we explain the comparative analysis of all algorithms. We have implemented image compression by applying lifting based discrete wavelet transform using Cohen-Daubechies- Feauveau 9/7 wavelet and the image coding techniques (EZW, SPIHT, and SPECK) on Intel(R) Core(TM) i3-2348M CPU @ 2.30GHz using Matlab R2017a installed in Linux Mint 18.3 OS. We have used a stan-dard test image called Lena of size 512 X 512 pixels grayscale image from the Waterloo Repertoire (available at http://links.uwaterloo.ca/) for evaluating the efficiency of algorithms. We have also evaluated the performance parameters of an image comresssion like PSNR, CR, Processing speed, and memory consumption. For each algorithms, we performed five levels of wavelet decomposition. The original Lena image, wavelet transformed, and reconstructed image are shown in Fig.9.

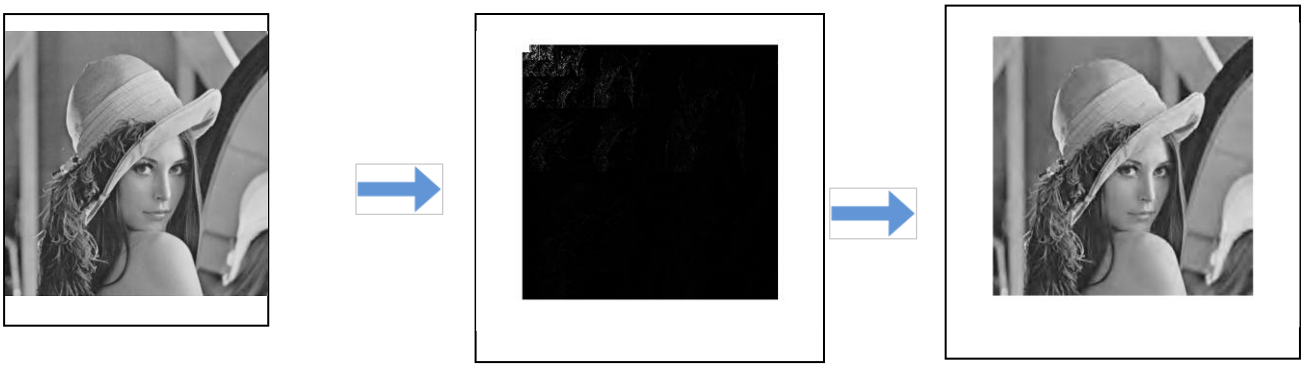


Fig. 9: (a) Original Lena image (b) Wavelet transformed Lena image (c) Reconstructed Lena image

A. Performance Evaluation Parameters

Performance of image compression techniques are described using the following features: Peak Signal to Noise Ratio (PSNR), compression ratio, processing speed, and memory requirements.

1) Peak Signal to Noise Ratio: PSNR is an important feature of an image compression algorithm. Compression efficiency of an image coder for a given bit rate is measured by Peak signal-to-noise ratio (PSNR). PSNR is used to measure the image quality. The PSNR ratio describes the image quality of the decompressed image to the original image. The higher the ratio is the better the technique. PSNR is calculated using equation (7).

$$\text{PSNR} = 10\log_{10}\frac{255^2}{\sum_{i=1}^{N}\sum_{j=1}^{N}(X[i,j]-X_{recons.}[i,j])^2} \qquad (7)$$

2) Compression ratio: CR is defined as the ratio of the number of bytes of the original image to the compressed image. It can also be described as the ratio of the size of original image to the size of the compressed image. The higher the compression ratio is the better the compression technique. The expression for Compression Ratio (CR) is given in Eq. (8). The higher the ratio is the better the compression technique.

$$CR = \frac{Number\ of\ bytes\ of\ original\ image}{Number\ of\ bytes\ of\ compressed\ image} \qquad (8)$$

3) Processing Time: We evaluated execution time using matlab command cputime to measure the time used by Matlab for the execution of algorithms thereby measuring efficiency of the techniques. Reduction in the processing time decreases the energy consumption of sensor node in WMSN.

4) Allocated Memory: We evaluated allocated memory using the built-in Matlab Profiler which return memory usage statistics, we have measured the memory allocated for all image coding techniques.

B. Comparative Analysis of EZW, SPIHT, and SPECK

This section discusses the comparative analysis of EZW, SPIHT, and SPECK for the following parameters: PSNR, CR, processing speed, and allocated memory. The comparison between the PSNR of the reconstructed images from EZW, SPIHT, and SPECK are shown in Fig. 10(a). It can be seen that the PSNR for SPIHT (30.53dB, 34.63dB, 38.10dB) and SPECK (31.36dB, 34.77dB, 37.67dB) which is nearly the same for bit rates 0.15bpp, 0.34bpp, and 0.71bpp respectively. The PSNR of EZW algorithm (29.46dB, 32.38dB, 34.15dB) for bit rates 0.15bpp, 0.34bpp, and 0.71bpp respectively which is lower compared to SPIHT and SPECK. The higher PSNR results into a better image quality. Fig. 10(b) shows the CR for all. Both SPIHT and SPECK have same CR for all bit rates. The CR of EZW is nearly the same compared to others. The time required for encoding SPIHT is (0.98 sec, 2.54 sec, and 7.9 sec) is very much less than compared to SPECK (3.46 sec, 5.62 sec, and 14.33 sec) and EZW (62.220 sec, 124.130 sec, and 232.45 sec] for bit rates 0.15bpp, 0.34bpp, and 0.71bpp respectively. The processing time required for both encoding and decoding of all are shown in Fig. 10(c) and Fig. 10(d). SPIHT is faster which implies the power consumed for performing image compression using SPIHT is very less. The allocated memory of all algorithms is large as shown in Fig. 10(e). But the memory consumption of SPIHT is small compared to others.

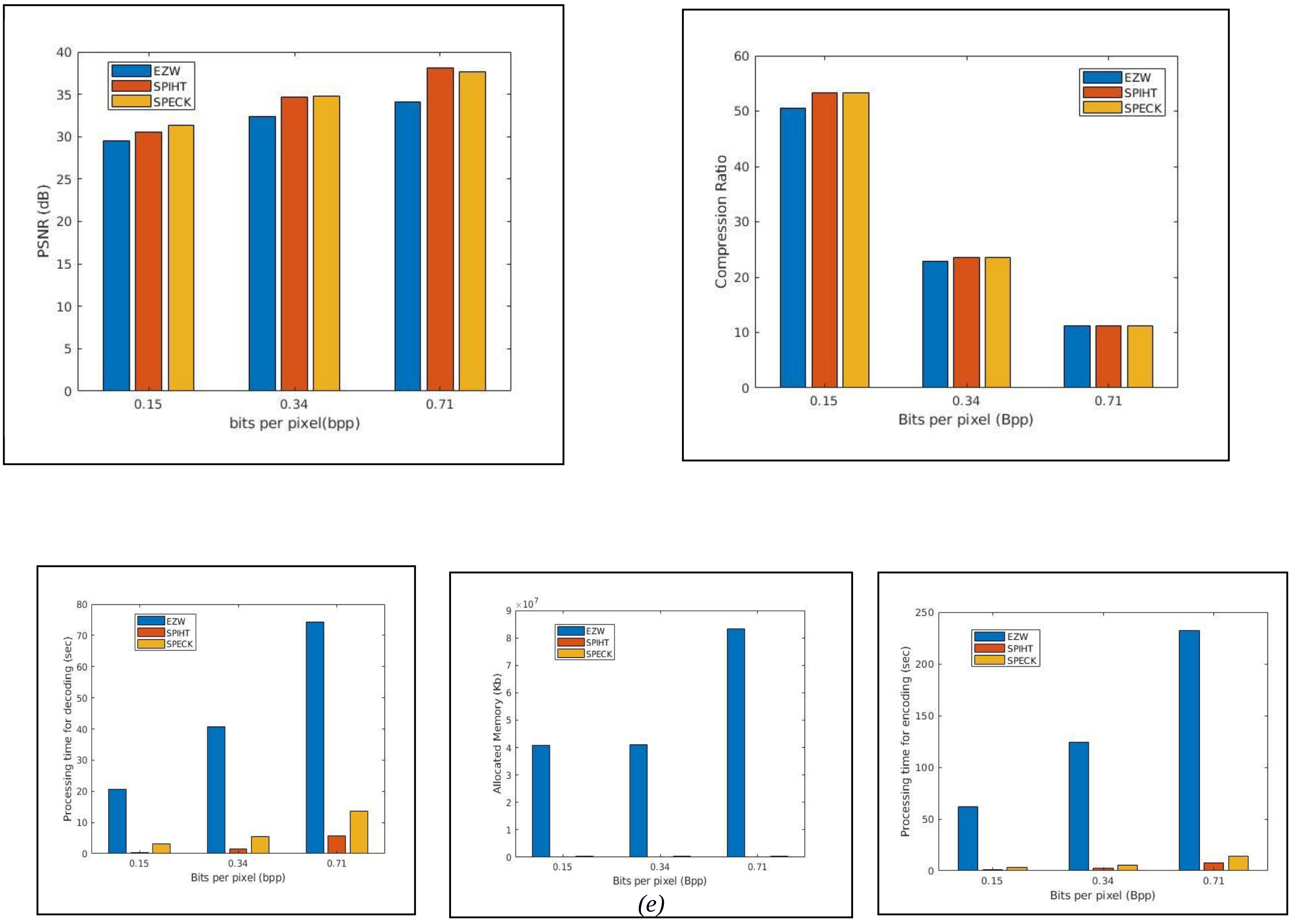


Fig. 10: (a) PSNR vs bit rate (b) Compression ratio vs bit rate (c) Processing time for decoding algorithm vs bit rate (d)Processing time for encoding algorithm vs bit rate (e)Allocated memory in Kbytes versus bit rate.

VI. CONCLUSION

In this paper, we have evaluated the performance parameters of EZW, SPIHT, and SPECK image coding techniques. Image quality using PSNR, compression ratio, speed of compression and memory consumption are the most important metrics we evaluated for compression performance. According to our matlab simulation results, SPIHT algorithm is superior over other image compression techniques. SPIHT algorithm has high compression ratio and low computational complexity in which these two parameters will help to reduce the energy consumed for transmission and energy required for processing respectively. Therefore, as SPIHT achieves embedded output bit stream, low bit rate, high compression ratio, efficient in terms of computational complexity, it is suitable to implement in WMSN which have some limitations in power consumption, proces- sor capabilities and low bandwidth. In the future, we will reduce memory requirement of image coder by developing low memory wavelet transform technique and modifiying SPIHT algorithm to further reduce memory.

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