3D Wavelets with SPIHT Coding for Integral Imaging Compression

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Summary

In three-dimensional display based on integral imaging (II) the compression of the elemental images is a major need to be implemented in real time applications. In this paper, we propose an Integral Imaging (II) lossless compression coder based on three-dimensional set partitioning in hierarchical trees,3D SPIHT. The elemental images are stacked to form a three dimensional image. 3D wavelet transform is performed, then 3D SPIHT coding is applied. Simulations are performed to test the performance of the 3D compression system. The results show that the proposed system has superior compression Performance compared to 2 DSPIHT.

Key words:

Integral Imaging, compression, 3D wavelet, 3D SPIHT

1. Introduction

Integral Imaging (II) has been one of the attractive autostereoscopic three-dimensional (3D) display techniques since it was proposed by Lippman in 1908 [1]. Integral Imaging [2]-[3] has many advantages such as full parallax, continuous viewing angle and full color display. In general, an integral imaging system [4]-[5] consists of two steps; pickup and reconstruction. In the pickup step, the rays coming from a 3D object through a lenslet array is recorded as elemental images representing different perspectives of a 3D object as shown in Fig.1.

Therefore, it has become a critical issue to handle such a large data for practical purposes such as storing on a media device or transmitting in real time. In general, the elemental images are very similar and there is a lot of redundancy between neighboring elemental images. So, II images exhibit high spatial correlation between adjacent elemental images. Accordingly, several approaches to effectively reduce the transmitted II images size by applying the conventional image compression techniques have been reported [6]-[16].

There are a lot of researches about using lossy compression techniques with 3D integral images. In [6]-[7], a three-dimensional discrete cosine transform (3D-DCT) has been used for this purpose. It was shown that the performance with respect to compression ratio and image quality is improved compared with that using JPEG. MPEG2 [8] and H.264 video encoder [9] are used to compress II images by rearranging the elemental images as the consecutive frames in a moving picture. However, the main deficiency is that video codec exploit the correlation between micro-images along one dimension only (the direction of the micro-images).Karhunen–Loeve transform (KLT) algorithm is also adopted for the compression of elemental array of images [10]-[11]. It gives good results but it suffers from the computational complexity of the KLT which makes it not practical for real time applications. Compression method [12] is adapted to integral imaging according to the optical characteristics of integral imaging, most of the information of each elemental image is overlapped with that of its adjacent elemental images. The method is to achieve image compression by taking a sample from the elemental image sequence for every m elemental image to get image compression. Recently, two wavelet-based lossy compression techniques for 3D integral images have been reported [13], [14] and [15]. The methods reported in [13] and [14] require the extraction of different viewpoint images from the integral image. A single viewpoint image is constructed by extracting one pixel from each micro-image, then each viewpoint image is decomposed using a Two Dimensional Discrete Wavelet Transform (2D-DWT). The lower frequency bands of the viewpoint images are assembled and compressed using a 3D-DCT followed by Huffman coding. It was found that the algorithm achieves better rate distortion performance, with respect to compression ratio and image quality at very low bit rate when compared to the 3D DCT based algorithms. The method reported in [15] uses a hybrid of techniques, which combines the discrete wavelet transform (DWT) and discrete cosine transform (DCT). It assumes a small number of micro-images typically 7×7, where each micro-image consists of a large number of pixels typically 208×208. In this case, it is reasonable to apply the 2D wavelet on micro-images followed by 2DCT .However, this kind of configuration requires a very coarse micro-lens pitch for the capture process which will result in very coarse integral images that are not suitable for 3D displays. The authors of this paper establish a compression algorithm [16] which is dependent on combining PCA

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with 2-D Discrete wavelet transform. It gives a good compression ratio and image quality compared to PCA compression alone.

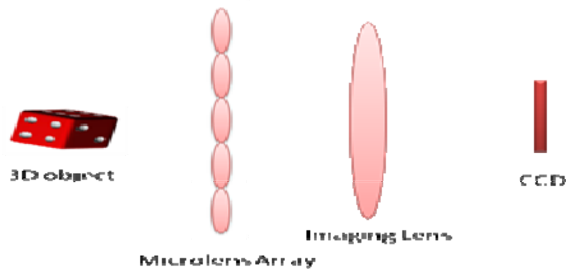


Fig. 1: Pickup of the integral image.

The presented work aims to introduce a compression technique that keeps a high compression ratio and at the same time reduces the number of bits required to represent an Integral Image by removing the spatial and spectral redundancies. 3D wavelet-based image compression algorithms [17]-[18] are particularly interesting because they can provide excellent rate-distortion performance and many attractive features. The three-dimensional Set Partitioning in Hierarchical Trees (3D SPIHT) based zerotree coding is the modern-day benchmark for video compression [19]-[20] which can provide the required low number of bits.

This presented technique relies on 3D SPIHT algorithm based on 3D dyadic wavelet transform for Integral Images. The elemental images are arranged to subsequent frames to make 3D image on which this technique is applied. And compare the result with the 2DSPIHT algorithm based on 2D discrete wavelet transform for the Integral Image.

The proposed algorithm is based on the 3D DWT transform to de-correlate the high cross-correlation between the sub-images generated by the micro-lens array. The scheme takes advantage of the viewpoints image representation of unidirectional images to decrease the number of bits required to code the image. However, this achieves a reduction in the bit rate and a significant reduction in the computational cost.

The paper is organized as follows: Section 2 gives an overview of the 3D DWT. Section 3 presents the SPIHT coding method. In Section 4 the proposed II compression algorithm is presented. Simulation results are discussed in Section 5. Section 6 concludes the paper.

2. RELATED WORK

2.1 3D Discrete Wavelet Transform

Wavelet transform (WT) represents an image as a sum of wavelet functions (wavelets) with different locations and scales [21]-[22]. Any decomposition of an image into wavelets involves a pair of waveforms: one to characterize the high frequencies corresponding to the detailed parts of an image (wavelet function) and one for the low frequencies or smooth parts corresponding to the approximation parts of an image (scaling function). The scaling function for multi solution approximation can be found out as the solution to a two-scale dilatation equation (e.g., see Eq. 1).

$$\phi(x) = \sum_k a_L \phi(2x - k) \qquad (1)$$

for some suitable sequence of coefficients a L(k) . An associated mother wavelet is given by a similar looking formula (e.g., see Eq. 2).

$$\psi(x) = \sum_k a_H \phi(2x - k) \qquad (2)$$

Wavelet analysis can be discovered with a filter bank which could be formed using the coefficient sequences aL(k) and aH(k) as shown in Fig. 2. The input sequence x is convolved with high-pass (HPF) and low-pass (LPF) filters aH(k) and aL(k) respectively and each result is down sampled by two, yielding the transform signals xH and xL. The choice of filter not only decides if the perfect reconstruction is possible or not, it also determines the shape of wavelet to be used to perform the analysis. By cascading the analysis filter bank with itself several times, a digital signal decomposition with dyadic frequency scaling known as DWT can be formed. An efficient way to implement this scheme using filters was developed by Mallat [23].

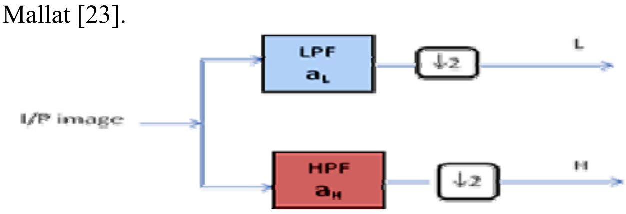
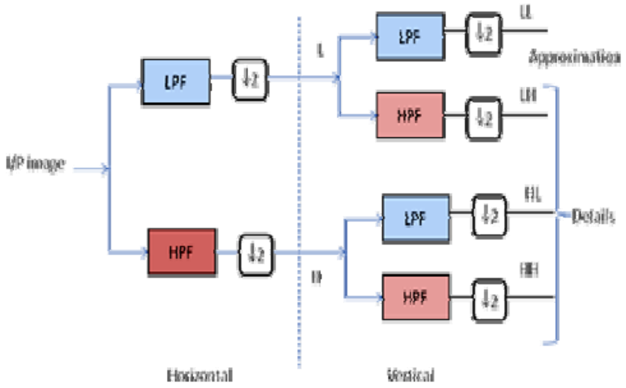


Fig. 2. Two-channel Filter Bank

The DWT for an image as a 2D signal can be obtained from 1D DWT. The easiest way for finding scaling and wavelet function for 2D is by multiplying two 1D functions. The scaling function for 2D DWT can be obtained by multiplying two 1D scaling functions: ϕ (x, y) = ϕ (x).ϕ(y). 2D DWT can be represented as a four channel perfect reconstruction filter bank as shown in Fig. 3(a).Now, each filter is 2D with the subscript indicating the type of filter (HPF or LPF) for separable horizontal and vertical components. The resulting four transform components consist of all possible combinations of high and low pass filtering in the two directions. By using these filters in one stage, an image can be decomposed into four bands. There are three types of detail images for each resolution: horizontal (HL), vertical (LH), and diagonal (HH). The operations can be repeated on the low low (LL) band using the second stage of identical filter bank. Thus, a typical 2D DWT, used in image compression, generates the hierarchical structure as shown in Fig. 3(b).

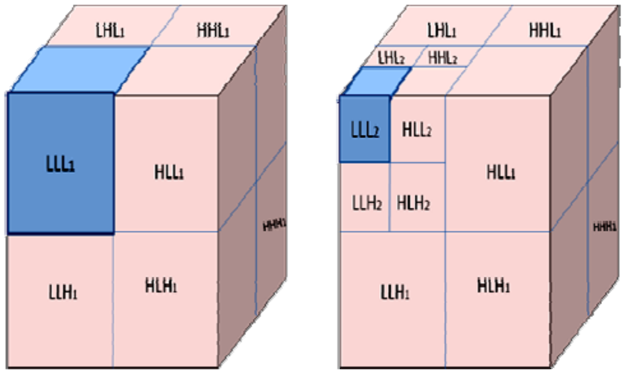


(a)

(b)

Fig.3.(a)2D Discrete Wavelet Transform (DWT) (b) Pyramidal Structure of Wavelet Transform

The Discrete Wavelet Transform (DWT) is a separable, dyadic tree-structured sub-band transform. The sub-band decomposition is performed by recursively passing the signal into a two-filter channel bank, where the successive decompositions are only done on the lowest sub-band. Since the 3D DWT is separable, a single step in the decomposition is composed of passing each dimension through the filter bank producing eight sub-bands per level. The 3D wavelet transform decomposes an image into a set of frequency sub-bands. In practice this is achieved by applying a series of filters with filter coefficients prescribed by the selection of a particular wavelet. The image is decomposed into 8 sub-bands as shown in Fig.4(a) that can be combined into a single structure having the same dimensions as the original image. In the case of a dyadic decomposition the lowest frequency sub-band is then further decomposed, often a number of times, in a recursive manner as shown in Fig.4(b).



(a) (b)

Figure 4 (a) 3D, 1 level wavelet decomposition, (b) Second level decomposition.

3. The Proposed 3D SPIHT Algorithm

3.1 Set Partitioning In Hierarchical Trees(SPIHT)

SPIHT algorithm was proposed by Amir Said and William Pearlman [24] and designed for optimal progressive transmission, meaning that we do not need the whole file to see the image. The image's PSNR will be directly related to the amount of the file received from the transmitter. This means that the image quality will only increase with the percentage of the file received. After the SPIHT transformation some regularities will exist in the file. These regularities may allow us to further compress the file. (SPIHT) is a wavelet-based image compression coder that offers a variety of good characteristics. These characteristics include:

- Good image quality with a high PSNR
- Fast coding and decoding
- A fully progressive bit-stream
- Can be used for lossless compression
- Ability to code for exact bit rate or PSNR

3.2 The Algorithm Steps

We have two algorithms the first algorithm for 2D SPIHT is implemented on the II image by making 2D DWT on the II image followed by the 2D SPIHT algorithm which is explained in the followed part. The proposed algorithm for 3D SPIHT on an II image consists of three steps as shown in Fig 5 The first step is to stack the II images into a sequence of frames that are composed of the elemental images as shown in Fig. 6. A 3D image is formed as shown in Fig.6. In the second step 3D wavelet transform on the 3D II sub-image then code the image using 3D SPIHT as shown in the third step as shown in Fig. 5.

Fig. 5 Steps of 3D SPIHT for II image

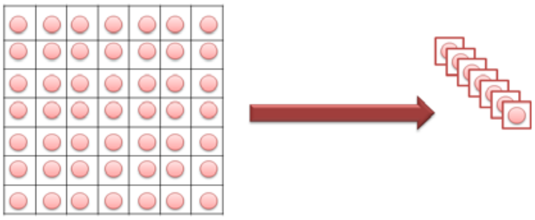


Fig. 6 Scan of the Integral Image

3.3 Mathematical Analysis of 2D SPIHT

Each parent coefficient at level n spatially correlates with 4 coefficients at level (n-1) of the same orientation. A coefficient at the lowest band correlates with 3 coefficients (Fig. 7).SPIHT achieves embedded coding in the wavelet domain using three lists: 1) the list of significant pixels(LSP); 2) the list of insignificant pixels (LIP); and 3) the list of insignificant sets (LIS).Where a set of tree coefficients is significant if the largest coefficient magnitude in the set is greater than or equal to a certain threshold (e.g., a power of two); otherwise, it is insignificant.

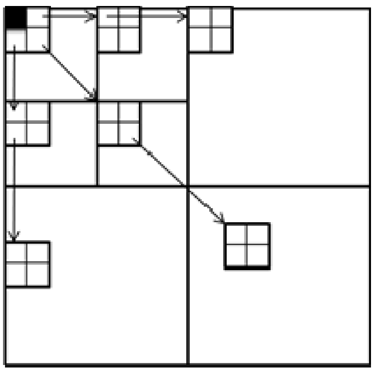


Fig.7: Parent- offspring in 2D SPIHT.

There are three important definitions in the 2D SPIHT parent-offspring relationship.

1. *O(i, j)*: Set of coordinates of all offsprings of node *(i, j)*.
2. *D(i, j)*: Set of coordinates of all descendants of the node *(i, j);*
3. *H(i, j)*: Set of coordinates of all spatial orientation tree roots;
4. *L(i, j)* : Set defined by $L(i, j) = O(i, j) - D(i, j)$

SPIHT considers two different types of zerotree: Type A tree is a tree where D(i, j)is insignificant (all descendants of (i,j) are insignificant), type B tree is a tree where L(i,j))is insignificant (all grand-descendants of (i,j) are insignificant).

Algorithm 1: 2D SPIHT

Step 1: (Initialization)

1. $n = \lfloor \log2 (\max \{c(i, j)\}) \rfloor$ where $c(i,j)$ is the coefficient
2. LIP = All elements in H
3. LSP = Empty
4. LIS = D's of Roots

Step 2: (Sorting Pass)

1. Process LIP.
   a) For *(i,j)* in LIP, S_n *(i,j)* is output where $S_n (i,j) = 1$ when $\max |c(i,j)| >= 2^n$ (significant) or $S_n (i,j) = 0$ for other (nonsignificant).
   b) If $S_n (i,j)=1$, sign of coefficient *(i,j): 0/1* is output and *(i,j)* is moved to the LSP.
2. Process LIS.
   a) For each entry *(i,j)* in LIS and if the entry is of type A then output $S_n(D(i,j))$.
      i) If $S_n(D(i,j)) = 1$ then for each $(k,l) \in O(i,j)$ output S_n(k,l).
      ii) If $S_n(k,l) = 1$, then add *(k,l)* to the LSP and output sign of coefficient: 0/1 .
      iii) If $S_n(k,l)=0$, then add *(k,l)* to the end of the LIP.
   b) If type B then output $S_n(L(i,j))$.
      i) If $S_n(L(i,j))$ =1 then add each $(k,l) \in O(i,j)$ to the end of the LIS as an entry of type A and remove*(i,j)* from the LIS.

Step 3: (Refinement Pass)

For each entry *(i, j)* in the LSP, except those included in the last sorting pass

output the n^{th} most significant bit of | c(i,j) |,

Step 4: (Quantization-Step Update)

Decrement *n* by 1 and go to Step 2

3.4 Mathematical Analysis of 3D SPIHT

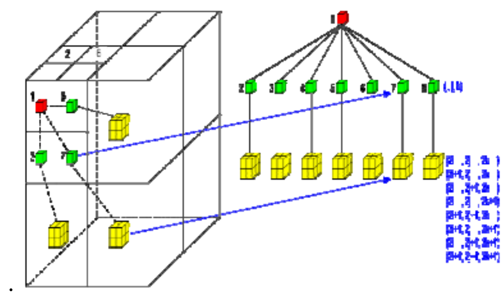


Fig. 8 Parent-child interband relationship and locations for 3D SPIHT coding.

In the 3D SPIHT scheme [25], each node has either no offspring (the leaves) or eight off-springs which constitute a group of 2x2x2 adjacent pixels. Hence, similar parent-offspring relationship can be established as shown in Fig. 8
The pixels in the highest level, and one of the pixels which has no 1 in each group has no offspring as in the 2D case. Fig. 8 depicts the parent-offspring relationship in the highest level of the pyramid.

Algorithm 2:3D SPIHT:

Step 1:Initialize to the number of bit planes

LSP = ϕ

LIP: all the coefficients without any parents (coefficients from the lowest frequency sub-band)

LIS: all coefficients from the LIP with descendants.

Step 2: Sorting Pass

For each entry (i, j, k) of the LIP

- If Output $S_t(i, j, k) = 1$,
  Move *(i, j, k)* in LSP and output the sign of $c_{i,j,k}$

For each entry *(i, j, k)* of the LIS

- If the entry is type A
  Output $S_t(D(i, j, k))$
- If $S_t(D(i, j, k))= 1$ then
  For all $(i', j', k') \in O(i, j, k)$
- If output $S_t(i', j', k')= 1$, add *(i', j', k')* to the LSP and output the sign of $c_{i',j',k'}$ else, add *(i', j', k')* to the end of the LIP
- If $L(i, j, k) \neq \phi$, move *(i, j, k)* to the end of the LIS as a type B entry.

Else, remove *(i, j, k)* from the LIS

– If the entry is type B

Output $S_t(L(i, j, k))$

If $S_t(L(i, j, k)) = 1$

· Add all the $(i', j', k') \in O(i, j, k)$ to the end of the LIS as a type A entry

· Remove *(i, j, k)* from the LIS

Step 3: Refinement pass

For all entries *(i, j, k)* of the LSP, except those included in the last sorting pass, output the t_{th} most significant bit of $c_{i,j,k}$

Decrement *t* and return to the sorting pass

3.5 Evaluation Metrics

Many metrics could be used to measure the error between the original image and the compressed image. One of the important metrics is the peak signal to noise ratio PSNR where (e.g., see Eq. 3).

$$PSNR = 10 \log_{10}\left(\frac{P^2}{MSE\ (CO, IN)}\right) \quad (3)$$

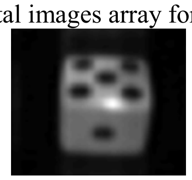
Where *P* is the maximum possible pixel value, *IN* is the original image, and *CO* is the compressed image and the *MSE* given by(e.g., see Eq. 4).

$$MSE = \frac{1}{XY}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1}\left[CO(x,y) - IN(x,y)\right]^2 \quad (4)$$

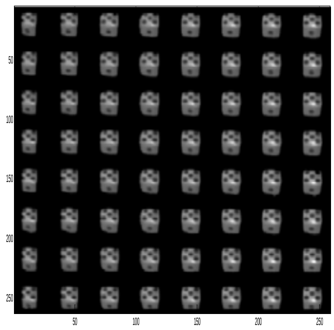
Where x and y are the spatial coordinates of images having a dimensions of X×Y pixels. The PSNR is calculated against the bit rate bit per pixel bpp.

4. Experimental Results

The experimental results for II compression using both3D SPIHT and the 2D SPIHT are presented. The used micro lens array has a total size of 10 cm by 10 cm and each lens has a diameter of 1mm and a focal length of 5.2mm.A 3D die object with a size of 10mm×10mm×10mm which is placed at a distance of 80 mm from the micro-lens array is used to evaluate the system performance. We had to use our own objects as there is no common data base of integral images for researcher to use and evaluate their results. The die image is special, because all the data in it is very important. If we lose any data, we cannot detect the numbers on it.
A total of 8×8 elemental images are used in the experiments, the total image size is 256×256 pixels in which each elemental image consists of 32×32 pixels. This image data is stored in a TIFF (tagged image file format).Fig.9 shows the used 3D object and the corresponding elemental images array for the used die.



(a)



(b)

Fig.9 (a) An image for the used die (b) The die elemental images array.

Five types of wavelets are used in the experiments. These are the Haar, Daubechies 2(db2), Coiflets (coif2), dmey, and the Biorthogonal 2.2(bior2.2) wavelets.

Fig. 10 shows a comparison between 2D SPIHT algorithm using different mother wavelet types at different bit rates. Fig. 10 shows that, at the bit rate smaller than 1 bpp all types give approximately the same result except the dmey type which gives the lowest value. At bit rates higher than 1 bpp, we find that the bior 2.2 gives the best results compared to the other types followed by db2 and the worst type is dmey.

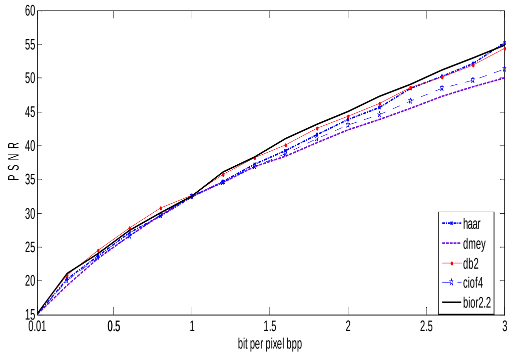


Fig. 10 PSNR versus Bit rate for the 2D SPIHT algorithm with different wavelet families

Fig 11 shows a comparison between 3D SPIHT algorithm using different mother wavelet types at different bit rates. Fig.11 shows that, the bior 2.2 also givesthe best results compared to the other types followed by db2 and the worst type is Haar at bit rateslower than 1.5 bpp and demy at the bit rateshigher than 1.5 bpp.

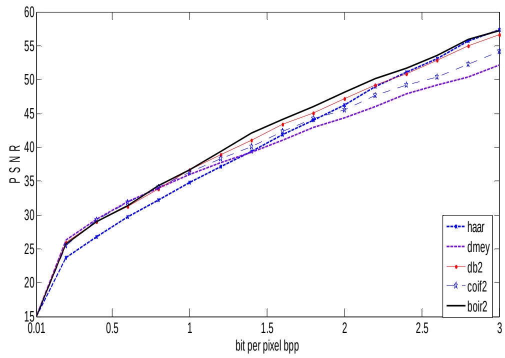


Fig. 11 PSNR versus Bit rate for the 3D SPIHT algorithm with different wavelet families

In the following experiments the Biorthogonal (bior2.2) wavelet is used. Fig. 12, Compares the PSNR for 2D SPIHT and 3D SPIHT at different bit rate values. From Fig. 12, it can be seen that the 3D SPIHT based algorithm shows a higher improvement in PSNR for all bit rate values compared to the previous 2D SPIHT scheme. We find that the 3D SPIHT algorithm gives higher PSNR value compared to the 2D SPIHT algorithm at all the different bit rates with approximately 5 db.

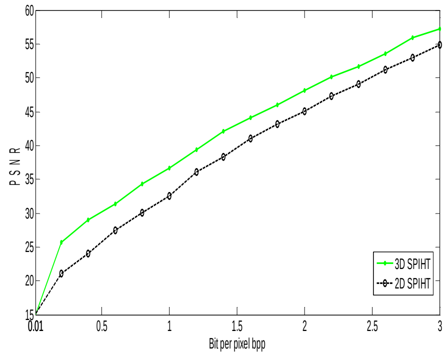
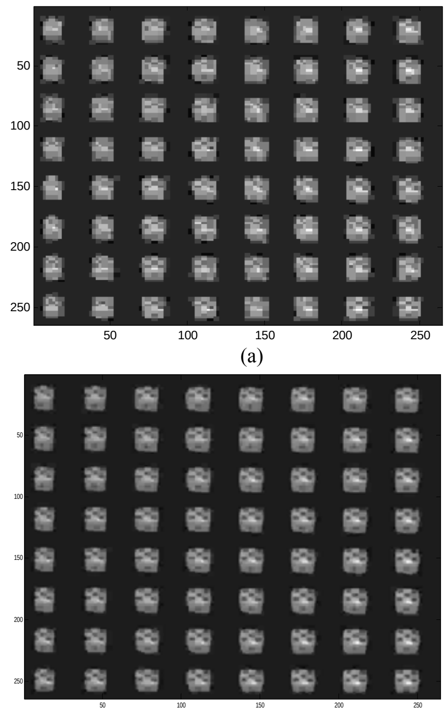


Fig. 12 PSNR versus Bit rate for the 3D SPIHT algorithm compared with 2D SPIHT algorithm



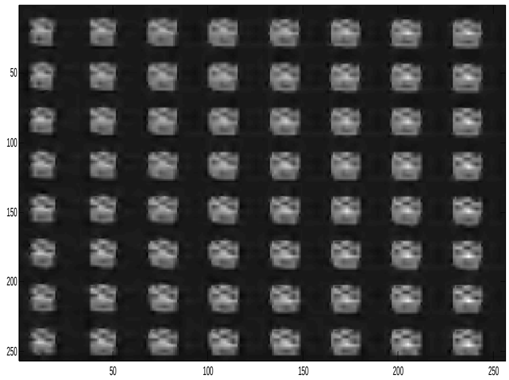
(a)

(b)

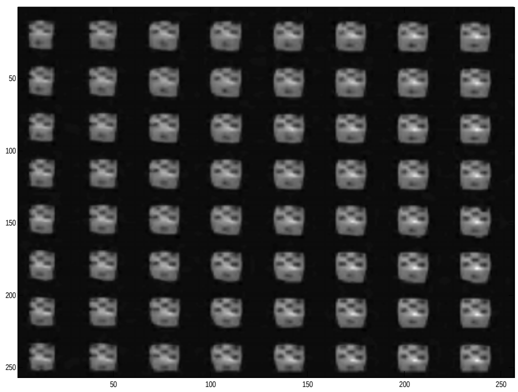
Fig. 13 a)The reconstructed II image for 2DSPIHTat 0.5 bpp PSNR=25.56 b)The reconstructed II image for 2DSPIHTat 1 bpp PSNR=32.42

In the first experiment, the reconstructed II image for both 2D SPIHT and 3D SPIHT for different compression ratios. Figures 13-a and 13-b show the reconstructed II image for 2D SPIHT for compression ratios of 0.5 bpp and 1 bpp respectively. As Fig. 13 shows, the PSNR equals 25.6 dB for 0.5bpp and equals 32.42 dB for 1 bpp.

Figure 14-a and 14-b show the reconstructed II images for different bpp using the proposed 3D SPIHT algorithm. As Fig. 14 shows, a PSNR of 30.64 dB and 36.64 dB are achieved for bit rates of 0.5 bpp and 1 bpp respectively.



(a)



(b)

Fig. 14 a)The reconstructed II image for 3DSPIHTat 0.5 bpp PSNR=30.64 b) The reconstructed II image for 3DSPIHT at 1 bppPSNR=36.64

From Fig 13 (a) the reconstructed die II image for 2DSPIHTat 0.5 bpp loses alot of data so we cannot identify the number on the die. Comparing figures 13(a) and 14(a) which shows the reconstructed die II image for 3DSPIHT at the same bit rate, we can find that the image using 3DSPIHT algorithm has much more details and the number of the die can be easily detected.

Conclusion

In this work, we present and evaluate a compression scheme based on applying the 3D wavelet transform with SPIHT on the Integral Images. The results are compared to II compression using 2D SPIHT. The proposed system performance is evaluated in terms of both bit rate and the recovered image quality. PSNR is used to evaluate the quality of the recovered image. The performance is also evaluated for different mother wavelet functions at different compression levels. The experimental results show that the bior2.2 wavelet gives the best results.3D SPIHT compression results show that the PSNR is 5 dB higher than 2D SPIHT for the used II images. At lower compression ratio the PSNR for 3D SPIHT is about 4 dB higher than 2D SPIHT. To conclude, the proposed technique indicates that using 3D SPIHT combined with 3D wavelets is a promising technique for II video compression.

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