A Combined Fractal and Wavelet Angiography Image Compression Approach

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Abstract: In this paper, a combined Fractal and Wavelet (CFW) compression algorithm targeting x-ray angiogram images is proposed. Initially, the image is decomposed using wavelet transform. The smoothness of the low frequency part of the image appears as an approximation image with higher self Similarities, therefore, it is coded using a fractal coding technique. However, the rest of the image is coded using an adaptive wavelet thresholding technique. This model is implemented and its performance is compared with best performances of the available published algorithms. A data set containing 1000 x-ray angiograms is used to study the performance of the algorithm. A minimum compression ratio of 30 with a peak signal to noise ratio (PSNR) of 36 dB and percent diameter stenosis deviation of (<0.2%) was achieved. Results demonstrate the effectiveness of the proposed technique in obtaining a diagnostic quality of reconstructed images at very low bit rates.

Keywords: X-ray images, Image compression, Fractal Analysis, Wavelet, Quality Measures.

1. INTRODUCTION

Advances in medical image generation made the demand to access, transfer, and interpret medical images in a faster, convenient, and accurate form a necessity. With the inevitable appearance of new medical commercial modalities such as x-ray angiography, CT imaging, MRI, and digital video; compression methods other than those currently utilized within DICOM standard will be necessary to meet requirements of remote medical facilities and to expedite data transmission among different medical centers. Presently, x-ray angiography is the mostly used non-invasive diagnostic and therapeutic technique for vascular diseases. Both diagnosis and therapy of vascular diseases require further processing and proper consultation with other medical centers. Therefore, an image compression that provides diagnostic quality at high compression ratio is vital. In recent decades, cardiologists and vascular surgeons have repaired the blood vessels and arteries of the heart using x-ray angiography procedure. Recently, x-ray angiography is utilized for therapy. However, in third world countries conventional x-ray angiography still has the major role in the detection, diagnosis and treatment of heart disease, heart attack, acute stroke and vascular disease.

Due to the large size of population who are diagnosed on daily basis to have different types of vessel problems, the need for reliable remote medical centers is imperative, and also because Coronary artery disease is the major cause of premature death in the United Kingdom [1], reducing the amount of data necessary to be sent based on an on-line scheme is necessary and requires an efficient medical image compression algorithm that is able to reduce the bit rate of transmission and to maintain the diagnostic quality of the images. On the other hand, dealing with the angiogram as it is requires higher storage memory or higher bandwidth for transmission. For example, a single patient digital angiogram video typically requires 7.5 Mbytes/s for 512 * 512 * 8-bit resolutions at 30 frames/s, resulting in 0.25 Mbytest/frame [2].

There are several techniques that have been used for medical image compression, but those that maintain the diagnostic ability for an image with an increase in compression ratio are required. Bearing in mind, the aim is to achieve a better compression ratio with minimal distortion requires the existence of reliable metrics to measure the diagnostic distortion rather than quantitative distortion. It also requires knowledge of the standards of image quality and how the compression technique is handled in digital medical imaging device. The most prime measures to be taken into considerations and must be correctly satisfied are: Peak Signal-to-Noise Ratio (PSNR), Signal-to-Noise Ratio (SNR), Peak Error (PE), Percent Root Mean Square Deviation (PRMSD), Normalized Sum Of Scores (NSOS), and Cross Correlation (CC).

Among compression techniques, recently two techniques are found to be the best in maintaining image quality and increasing compression ratio, these are Wavelet and Fractal techniques.

Wavelet analysis has generated much interest in both theoretical and applied mathematics over the past decade. It is a time-scale representation that has been used successfully in a wide range of applications. Wavelet transformation consolidates image energy in few coefficients with excellent localization characteristics in the spatial-frequency domain [3]. To compress the image, these coefficients will go
through a thresholding process depending on the criterion chosen to ignore the less significant coefficients. For reconstruction, an inverse Wavelet transform to the thresholded coefficients is applied. The result will lead to a compression ratio lower than 1.4 for an original angiogram image with different biorthogonal filters [4]. The problem with this transform is that it needs a very high threshold for the approximation coefficients; hence no compression is achieved for these coefficients, this is considered as a constrain point for this method.

Fractal Compression was first promoted by M. Barnsley [5]. Fractal encoding depends on the assumption that natural and most artificial objects contain similar redundant repeating patterns called fractals [6]. The basic idea of fractal transform was built on the self-similarity of the objects that allows saving a small portion of the object instead of the whole object. The problem in fractal compression is its time consumption, where it is very slow in analyzing the data for large images.

A combined ‘Fractal and Wavelet’ (CFW) compression algorithm is proposed in this paper. It maximizes the advantages of Fractal and Wavelet methods and gets rid of their disadvantages. However, combining wavelet and fractal is not new but it depends on utilized criteria for hybriding.

One of these techniques is based on compressing high frequency wavelet coefficients by using a modified fractal-coding algorithm and coding the low frequency wavelet coefficients by a lossless method called BTPC [7]. Another criterion is introduced in the Hybrid Fractal Zero-tree Wavelet Image Coding which couples a zero tree-based encoder, such as the embedded zerotree wavelet (EZW) coder or set partitioning in hierarchical trees SPIHT and a fractal image coder [8]. The idea is based on applying a locally optimal distortion-rate calculation for trading in similar structures in EZW and tree-based fractal encoders. The coder that performs efficiently is adaptively selected. A fractal coder usually performs better with edges and texture areas of an image [9]. The best achieved PSNR ranged between 26.49dB and 39.28 dB [8].

The rest of the paper is divided into five main sections: compression techniques, proposed approach, quality of decompressed images, achieved results, discussions and conclusions. Section 2 covers the recent developments in fractal and wavelet based image compression and coding techniques. Section 3 lays out the foundation for the proposed combined fractal wavelet compression approach and it is implementation. Section 4 introduces quality performance measures that will be used to validate the proposed approach. It discusses both subjective and objective quality measures. Implementation and results are covered in section 5. Manifestation and efficacy of the proposed technique are highlighted. Moreover, comparisons among medical image compression techniques are also studied. Section 6 explains the obtained results and concludes main achievements of this codec followed by references.

2. IMAGE COMPRESSION TECHNIQUES

The era of advanced communication systems, satellite communications, and mobile telecommunication paced the birth of new research in image compression literature.

Wavelet and fractal image compression techniques gained further momentum in its development for their ability in producing high compression rates with perceptually relevant quality. Advances in both compression areas are considered as the base for this current research. Therefore, background analysis of recent emerged compression techniques in wavelet and fractal domains will provide an insight to the proposed technique and strengthen its achievements.

2.1. Image Compression in Wavelet Domain

Wavelet is the base of multiresolution image decomposition which allows efficient subband coding [10]. It reveals strong space-frequency localization where relevant features within each subband and similar features across subbands are clustered [11]. Wavelet subbands are statistically dependent making it very suitable for efficient coding [12]. The pyramidal, or dyadic wavelet decomposition, in particular, illustrated excellent energy compaction. EZW encoder is the first to utilize this property. It uses both bit-plane coding and the zerotree configuration [13]. Said and Pearlman partitioned the embedded tree and proposed the set partitioning in hierarchical trees (SPIHT) encoder [14]. EZW has excellent rate-distortion (R-D) performance and low computational complexity EZW coders are progressive coders in which data can be transmitted and encoded at any target bit rate. However, exploiting the wavelet tree in adaptive manner could improve the compression results and provide low rate at a higher computational costs. This Adaptive concept is employed non-progressively in Xiong et al. [15]. Although their algorithm provides better compression results compared with non-adaptive EZW coders its computational complexity is extremely high. It is worth mentioning that both types of coders are still focusing on the inter-subband correlation. Another type of coders that base their compression on a structure-like mechanism is recently evolved. The layered zero coding (LZC) algorithm proposed by Taubman and Zakhor [16] for still and video images represents a good example of structure-like compression approach that efficiently incorporates an adaptive arithmetic coding [17]. Other algorithms that exploit the wavelet domain do exist among these algorithms are those that concentrate on the morphological representation [18, 19], classification of image subbands [20], and estimating the statistical properties of coefficients in the subbands [21, 22]. The latter are called backward adaptive techniques and demonstrated superior rate-distortion performance in comparison with forward adaptive ones. However, they still suffer from higher computational complexity at the decoder side.

2.2. Fractal Image Compression and Wavelet Domain

Fractal image compression is based on exploiting the self-similarity between different image patterns. Redundant information within the spatial image is effectively reduced using this technique [23, 24]. Recent results showed that applying fractal coding in wavelet domain using self-similarities within and across wavelet trees gives better compression results compared to classic compression schemes as well as simple fractal coding schemes. This is due to its capabilities to eliminate blocking effect and to provide more efficient coding for the quantized coefficients.
3. COMBINED FRACITAL WAVELET COMPRESSION APPROACH

The proposed compression approach, as shown in Fig. (1), depends on maintaining the properties of wavelet transform coders in minimizing the bit quota for non-significant coefficients and maintaining the most significant parts of the wavelet subbands at lower costs. Moreover, it is expected to utilize the efficiency of fractal image compression in detecting similarities and their efficient encoding. In the following subsections the wavelet decomposition procedure, fractal image compression, and proposed encoding scheme are further explained and clarified.

3.1. Compression of the High-Resolution Subbands in Wavelet Domain

Natural images usually have smooth color variations, with the fine details appear as sharp edges in between the smooth variations. Technically, smooth objects in an image represent low frequency contents while fine details represent high frequency variations. Decomposing the image into its smooth variations and details can be obtained simply by using a Discrete Wavelet Transform (DWT) [10]. The decomposition process is divided into several levels. Each level will produce a two-dimensional array of coefficients containing four bands of data. These bands are labeled as LL (low-low), HL (high-low), LH (low-high) and HH (high-high) respectively. The next level will decompose the LL band again in the same manner, thereby producing even more sub bands. This process can be repeated up to any level, thereby resulting in a pyramidal decomposition. Fig. (2) shows a five-levels wavelet decomposition of an angiogram image.

The LL band at the upper level of decomposition is classified as the highest energy band with smooth visitations, and the other 'detail' bands are classified as lower energy bands with sharp variations. As it is obvious from Fig. (2), the degree of energy compaction is decreasing from the top of the pyramid to the bands at the bottom [10]. Moreover, further decomposition will not reveal further information regarding the image. After decomposing the image into sublevels, a stream of coefficients will appear. A few of these coefficients contain the most energy of the image while others appear as less significant details. Hence, the aim is to extract the significant coefficients, which contain most of the...
energy, and ignore the others. Regardless of the adopted compression scheme in the wavelet domain, if used as is, the low-resolution subband which contains most of the energy of the image and characterized by its smooth variation will consume most of the bit quota. Therefore, to effectively utilize the properties of the fractal image compression this part is coded separately using fractal image coding. Other parts of the image that contain more coefficients but at low amplitude levels will be coded efficiently using the wavelet domain only. To achieve this, after decomposing the image signal into sublevels an appropriate threshold \( \text{thr} \) is needed to control the compression rate and the quality of the detailed sub images. Thresholding is a process that compares some given values to a reference value \( \text{thr} \). A hard thresholding concept is used in compressing the details of the image which is described as setting the values that are less than the reference value to zero, and keeping the other values, which are greater than this value, to their original value. Hard thresholding process is illustrated as follows, assume that \( x(n) \) is a detailed wavelet coefficient and \( x'(n) \) is the coefficient after thresholding:

\[
\begin{align*}
\text{If } |x(n)| > \text{thr} & \quad \text{then } x'(n) = x(n) \\
\text{Else} & \quad x'(n) = 0
\end{align*}
\]

After defining the thresholding process, the criterion for finding the threshold value \( \text{thr} \) is the next step. Different techniques are used to calculate the threshold value. One of these techniques is based on the energy requirements. Therefore the way in choosing the threshold value depends on the total energy of the detailed sub images. In order to calculate a threshold based on a certain portion of the energy, the following steps are performed:

- Calculate the total energy of each subband, \( E_{Ti} \), using the wavelet coefficients \( x[n] \), as follows:

\[
E_{Ti} = \sum_{n=1}^{L_i} x^2(n)
\]

- Calculate the desired energy in the thresholded coefficients, \( E_{pi} \), i.e.:

\[
E_{pi} = \sum_{n=1}^{P_i} x^2(n)
\]

- To determine the value \( pi \) and the threshold, the following steps are conducted:
  a. Sort the wavelet coefficients in descending order based on its energy, \( x_{\text{sort}}[n] \).
  b. Apply the following procedure:

```plaintext
[Ed = Percentage of \( E_t \) * \( E_r \)]
energy = 0; p = 0;
while energy < \( E_x \)
    energy = energy + \( (x_{\text{sort}}[p])^2 \);
    p = p + 1;
end
thr = abs(\( x_{\text{sort}}[p] \))
```

Fig. (2). Five Levels Pyramidal Decomposition of an Angiogram.
If the overall distortion is within the accepted rate-distortion criterion, significant coefficients will be separately encoded using adaptive differential run length and progressively transmitted. Otherwise, other percentage is used and the same procedure is repeated until the criterion is satisfied [35].

### 3.2. Compression of Low-Resolution Subband Using Fractal Image Compression

Efficiency of fractal transform coder is gained due to the availability of self-similarity of the objects allowing the coder to reduce the needed space for the whole object and only code a small portion of it. Self-similarity is not fully maintained in natural images, however, some portions of the image are self similar. Lena image, for example, does not contain the type of self-similarity which is found in the Sierpinski triangle [5]. However, self-similar portions of the image are clear in it. These detected parts are not exactly the same due to the affine transformation process applied to them. This means that the results of the encoding process will not be an identical copy of the original image. However exploiting self similarities within the whole image would effectively reduce its desired bit quota. On the other hand, if the image is decomposed using wavelet transform and lower resolution portion of it is utilized for fractal encoding, the encoder will be more efficient due to the maximized similarities within smooth objects and to their energy compaction dominance. Moreover, to resolve the non-identical coding of similar objects due to transformations, a segmentation process is proposed. Segmentation will further enhance the performance of the fractal coder. Fractal compression for low resolution wavelet image is conducted as follows:

#### 3.2.1. Encoding Scheme

##### 3.2.1.1. Segmentation

An image is regularly segmented into blocks. Fig. (3) shows the segmentation of the image into range blocks. Each block is a two-dimensional array of BxB pixels. These blocks are called range blocks. Each range block is arranged in a 1-D sequence of a row followed by another row order. The whole 2D array of range blocks is then represented by 1D sequence, i.e. $R = \{R_i\}$ [7].

##### 3.2.1.2. Creating Domain Block Pool

The pool of the set of domain blocks contains 2Bx2B squares covering the whole of the original image. This pool is generated by sliding a 2Bx2B window within the original image and skipping $\Delta$ pixels from left to right, top to bottom. Also each domain block is transformed in 8 different ways. So, this will produce a huge pool of domains.

##### 3.2.1.3. Affine Map

For each range block, a domain block and map need to be specified, so that range block and domain block become the best pair. To minimize the delay due to calculations, the domain block is down sampled to be equal to the range block size of BxB pixels. For each best pair of range and domain mapping coefficients are saved. These coefficients include the location of the domain, the transformation type of the domain, the contrast of the domain, and the offset of the range.

##### 3.2.1.4. Extracting the Non-Similar Part

In the case where a block is uniquely identified, each range block that does not pair with a domain block is marked as a non-similar part. To avoid losing such data, all of these ranges are losslessly coded and sent as is. This would introduce an overhead problem if the number of non similar blocks covers the whole image. Such situation is almost impossible.

#### 3.2.2. The Decoding Scheme

The contractive mapping theorem is utilized to decode the image. The decoding process starts by any image, for example rectangle. The decoder maps the mapping coefficients to the initial seed image iteratively. This process converges to fixed point of the mapping coefficients, once the compressor has found good mapping coefficients for the image. To perform an iteration of the mapping coefficients,
the decoder takes the list of all affine maps and applies each one in turn. This converts a set of domains into a set of ranges. Since no overlapping is allowed between range blocks, the whole image will be covered. Therefore, a new complete image is produced as a result. The decoder will repeat the whole process until convergence is achieved. That is, until there are a little difference between the output of the current iteration and its input image. Convergence is usually very fast and is obtained by 3 to 6 iterations.

4. QUALITY OF THE RECONSTRUCTED IMAGES

The quality of the reconstructed image and the compression ratio determine the performance of the compression scheme. Due to the reduction of the CFW coefficients the reconstructed signal will suffer a reduction in its quality. Therefore there must be some quality measures that evaluate the quality of the reconstructed image. Two types of evaluation mechanisms are found in the literature and utilized to validate the efficacy of the proposed algorithm [36].

4.1. Subjective Evaluation Technique

In this part, an observer is asked to evaluate the compression algorithm by following some rules. However, variations among different observers recommend applying objective measures that will rate the quality based on mathematical formula.

4.2. Objective Quality Measures

Several measures can be incorporated to evaluate the performance of the proposed compression algorithm. In this paper the following measures are used:

4.2.1. Calculating the Peak Signal to Noise Ratio (PSNR):

Calculating the PSNR gives a clear mathematical evaluation of the amount of destruction affected to the original signal. The calculation of the PSNR is as follows:

$$PSNR = 10 \log_{10} \left( \frac{255^2}{\text{variance}(x - x_r)} \right)$$

where \( x \) is the original signal, and \( x_r \) is the reconstructed signal. The 255 represents the highest level of an 8-bit image. For other image format, it will be \( 2^{N_b} - 1 \), where \( N_b \) is the number of bits/pixel of the image.

4.2.2. Calculating the Signal to Noise Ratio (SNR)

The SNR is an important measure for any system, it simply indicates the ratio of the input signal to the noise, which is always must be high enough. The calculation of the SNR is as follows:

$$\text{SNR} = -10 \times \log_{10} \left( \frac{\text{variance}(x - x_r)}{\text{variance}(x)} \right)$$

4.2.3. Calculating the Peak Error (PE)

Peak error provides the maximum available error. A reduced value indicates that the distortion is reduced. Calculation of the PE is defined as follows:

$$\text{PE} = \max (x - x_r)$$

4.2.4. Calculating the Partial Root Mean Square Difference (PRMSD)

The calculation of the PRMSD is as follows:

$$\text{PRMSD} = \sqrt{\text{variance}(x - x_r)}$$

4.2.5. Calculating the Normalized Sum Of Scores (NSOS)

The calculation of the NSOS is done as follows:

$$\text{NSOS} = \frac{\sum (x-x_r)^2}{\sum x^2}$$

4.2.6. Calculating the Cross Correlation (CC)

It measures the amount of similarity between original and reconstructed signal. It is limited in absolute form between zero and one. When the value is very close to one it means that the two images are identical as it goes toward zero it means that images are dissimilar. The calculation of the CC is done as follows:

$$\text{CC} = \frac{\sum (x \times x_r)}{\sqrt{\sum x^2 \sqrt{\sum x_r^2}}}$$

5. IMPLEMENTATION AND RESULTS

In this section, the proposed simulation model used in computer implantation is described. The results obtained will also be presented.

5.1. Implementation

The CFW algorithm is implemented on Matlab 7.0 where a graphical user interface GUI application is created. Fig. (4) shows the simulation model. The software initially calls the angiographic image to be compressed. Three compression approaches are available: wavelet, fractal, and combined fractal wavelet. The package enables the use of both orthogonal and bi-orthogonal wavelets. All the parameters in the package is either automatically selected to produce the best R-D or manually selected by the user. The package provides rate and objective quality measures for the reconstructed image and allows the generation of a report of the results.

5.2. Results

To demonstrate the capability of the proposed CFW coder in providing proper compression ratio at an acceptable image quality, a randomly selected angiogram is used. The angiogram is compressed using the designed package. The user can either use a global threshold that is obtained using equation 4 or local thresholds per sub-band as clarified in section 3.1. Moreover, the package can decompose the image into any specified number of levels by using either available wavelet filters or specically provided wavelet filters. For demonstration purposes a 4-level wavelet decomposition is performed using bior4.4 wavelet filters. The result of applying the CFW coder of this example is shown in Fig. (5). It is worth mentioning that the global threshold is the minimum maintained detailed wavelet coefficient. Other
Fig. (4). Graphical user interface of the CFW algorithm.

Fig. (5). Demonstration of the CFW on an angiogram image. Both original and compressed images are shown.

Fig. (6). Performance of CFW coder using different quality measures.

coefficients are considered non-significant. To study the impact of the global threshold on the results obtained using the CFW coder. Fifty images are compressed using CFW coder. The wavelet coder uses the bior 4.4 wavelet filter with 4 levels. The fractal coder uses range = 8, Domain = 16, step size = 16, and an acceptable error = 25. For each global
has the best PSNR at 32.76 dB. To study the effect of the different wavelet filters are used. The results are the performance of the algorithm at a compression ratio of the proposed algorithm provides better qualities for the wavelet coder. Table 2, the proposed algorithm is evaluated using a PC with AMD/Athlon 2.0 GHz processor. To show the capability of the proposed algorithm in comparison with well known compression schemes, the algorithm is compared with SPIHT, JPEG2000, and DCT-CSIHT respectively [14], [37, 38]. Table 2 shows the PSNR for different compression methods at various Bit rates. As it is clearly obvious from Table 2, the proposed algorithm performs better than all of the considered algorithms. Table 2 shows a comparison between the results of the proposed algorithm and those results achieved by other compression algorithms. As it can be depicted from Table 2, the proposed algorithm provides better qualities for the same results. CFW outperforms SPIHT, JPEG2000, and DCT-CSIHT respectively. The result clearly demonstrates that the incorporation of fractal compression provides a substantial performance improvement for the wavelet coder. Another important aspect of Image compression is the speed of encoding and decoding of the compression algorithm. 50 images are used to study this parameter. Table 3 shows a comparison of the encoding/decoding speeds for different algorithms [39]. To study the impact of the wavelet filter on the performance of the algorithm, 100 images are used to test the performance of the algorithm at a compression rate of 40. Four different wavelet filters are used. The results are summarized in Table 4. As shown in Table 4, the Bior4.3 filter has the best PSNR at 32.76 dB. To study the effect of the compression scheme on the quality of x-ray angiograms, a 1000 x-ray images are compressed using the compression algorithm such that a minimum PSNR is 36 dB. The minimum compression ratio achieved was 30. The reconstructed images are then evaluated using Quantitative coronary Analysis (QCA) to determine the effect of compression on stenosis. The maximum deviation between the original and compressed diameter was less than 0.2% [40].

6. DISCUSSION AND CONCLUSIONS

Wavelet-based coders are initially introduced, discussed and implemented. Fractal image compression techniques are also investigated and implemented. A combined fractal wavelet image coding algorithm is then proposed. It couples morphological wavelet and fractal image coding. The new coder represents the cream of the cream of fractal and wavelet coders. On the contrary, it allows simple reconstruction and includes a developed rule to estimate the amount of overhead information and the amount of bit rate savings achieved by applying the fractal coding for the low resolution wavelet sub image. In case such overhead is high or no bit rate saving is achieved only lossless wavelet coder is used. Limitations are investigated and implemented. A combined fractal wavelet image coding algorithm is then proposed. It couples morphological wavelet and fractal image coding. The new coder represents the cream of the cream of fractal and wavelet coders.

Table 1. Impact of Global Thresholds and Quality Measures of CFW Coder

<table>
<thead>
<tr>
<th>Threshold</th>
<th>CR</th>
<th>PSNR</th>
<th>SNR</th>
<th>PE</th>
<th>PRMSD</th>
<th>NSOS</th>
<th>CC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4</td>
<td>121.5247</td>
<td>28.6402</td>
<td>13.6154</td>
<td>245.0201</td>
<td>0.208566</td>
<td>0.011426</td>
<td>0.994271</td>
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<tr>
<td>0.6</td>
<td>90.07224</td>
<td>30.97962</td>
<td>15.95456</td>
<td>209.7514</td>
<td>0.159321</td>
<td>0.006667</td>
<td>0.996661</td>
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<tr>
<td>0.7</td>
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<td>32.26719</td>
<td>17.24213</td>
<td>210.0792</td>
<td>0.13737</td>
<td>0.004957</td>
<td>0.997519</td>
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<tr>
<td>0.8</td>
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<td>34.0354</td>
<td>19.01034</td>
<td>156.3222</td>
<td>0.112068</td>
<td>0.003299</td>
<td>0.99835</td>
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<td>21.8944</td>
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<td>0.080404</td>
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<td>0.059307</td>
<td>0.000924</td>
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<td>0.98</td>
<td>13.68077</td>
<td>42.50832</td>
<td>27.48327</td>
<td>22.90599</td>
<td>0.042251</td>
<td>0.000469</td>
<td>0.999766</td>
</tr>
</tbody>
</table>

Table 2. The PSNR for Different Compression Method at Various Bit Rates

<table>
<thead>
<tr>
<th>Image Type</th>
<th>Bit Rate (pbb)</th>
<th>Algorithm Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angiogram</td>
<td></td>
<td>SPIHT</td>
</tr>
<tr>
<td>0.025</td>
<td>0.40 33.4</td>
<td>0.40 36.1</td>
</tr>
<tr>
<td>0.10</td>
<td>0.40 40.3</td>
<td>0.40 44.1</td>
</tr>
<tr>
<td>0.24</td>
<td>0.40 45.4</td>
<td>0.40 47.6</td>
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<tr>
<td>0.50</td>
<td>0.40 49.8</td>
<td>0.40 50.5</td>
</tr>
</tbody>
</table>
REFERENCES


Table 3. The Average Encoding/Decoding Time in Seconds

<table>
<thead>
<tr>
<th>Algorithm Method</th>
<th>SPIHT</th>
<th>JPEG2000</th>
<th>WCAP40</th>
<th>Proposed CFW</th>
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</thead>
<tbody>
<tr>
<td>Time (sec)</td>
<td>2.3/2.7</td>
<td>1.1/1</td>
<td>5.4/2.9</td>
<td>1.0/0.87</td>
</tr>
</tbody>
</table>

Table 4. The Average PSNR Values in dB Using Different Wavelet Filters at Compression Ratio of 40:1

<table>
<thead>
<tr>
<th>Image Type</th>
<th>Wavelet Filter</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 Angiograms</td>
<td>Symlets 5</td>
</tr>
<tr>
<td>PSNR (dB)</td>
<td>32.68</td>
</tr>
</tbody>
</table>

CONFLICT OF INTEREST

The authors confirm that this article content has no conflicts of interest.

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Declared none.


