Adaptive RLE-Huffman Lossless and Diagnostically Lossless Compression for Pharynx and Esophagus Fluoroscopic Images

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Abstract

Diagnostic imaging devices such as fluoroscopy produce a vast number of sequential images, ranging from localization images to functional tracking of the contrast agent moving through anatomical structures such as the pharynx and esophagus. In this paper, an effective method for lossless and diagnostically lossless compression of fluoroscopic images is proposed. The two main contributions are: (1) compression through block-based subtraction matrix division and adaptive Run Length Encoding (RLE), and (2) range conversion to improve the compression performance. The region of coding (RC) – in this case the pharynx and esophagus, is effectively cropped and compressed using customized correlation and the combination of Run-Length Encoding (RLE) and Huffman Coding (HC), to increase compression efficiency. The experimental results show that the proposed method is able to improve the achieved compression ratio by 488% as compared to that of the benchmark traditional methods.

INTRODUCTION

The advancement in non-invasive examination provides medical practitioners with a high level of detailed diagnostic information without surgical procedures, thus maintaining patient comfort and reduced recovery time. Arising from the introduction of such devices, clinics, medical centers and hospitals have seen an immense increase in the use of diagnostic imaging that result in a colossal number of images in their archives from the many series of images produced in each examination. This has led to increasing loads of handling and costs, processing, transmission and storage.

Although computer software and hardware technologies have increased rapidly, medical institutions are facing an uphill battle striving to cope with the immense volume of new images generated daily. Such large amounts of data require large storage facilities for these digital images. Furthermore, high-end networks are required for digital transfer and especially in telemedicine.

Image compression is advantageous in decreasing the storage resources required for the medical images (Bairagi and Sapkal 2012). It also decreases the bandwidth required for communications, where, smaller files take up less processing resources. The decisive compression technique for medical images is lossless, where redundancy in the data is removed without reducing the image quality, allowing for the images to be reconstructed to its original state upon decompression (Sahu and Kamargaonkar 2013; Ukrit, Umamageswari, and Suresh 2011). However, the fascination for most researchers seeking a further solution is lossy compression as it enables attaining higher compression ratio, further reducing the file size. Unfortunately, lossy compression is known to degrade image quality, hence the reconstructed image is not an exact match of the original. This has posed issues in the medical field in terms of the validity of the reconstructed images. Consequent, proponents of the use of lossy compression in (Ukrit, Umamageswari, and Suresh 2011; Choong, Logeswaran, and Bister 2006) have tried to legitimize the applicability of lossy compression in medical diagnosis by indicating that lossy compression is effective in the removal of noise that arise due to the flaws of the imaging equipment and other ambient influences. In a double-blind test conducted, the medical practitioners considered the controlled lossy compressed images as more accurate as compared to the original images (Choong, Logeswaran, and Bister 2006).

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**Background:**

Medical images can be categorized into two main categories: (1) a single or limited number of independent images per examination as in the case of X-ray; and (2) sequential images that are produced by the Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Fluoroscopy and other such imaging modalities. Fluoroscopy is a specific type of X-ray that provides series of images of a patient’s organ structure in real-time. It is used in many types of procedures, including Barium Swallow, Percutaneous Nephrostomy (PCN) and cardiac catheterization. Fluoroscopy images are used to provide interpretive data to surgeons during an operation. However, these images can be very tricky for a computer to interpret as each pixel represents the entire path of tissue, air, and bone travelled by the X-ray from the source to the detector plate (Mei-Yen et al. 2007; Russakoff, Rohlfing, and Maurer Jr 2002).

Segmentation partitions an image into parts or objects. The quality and noise present in the image, determines the need for pre-processing or post-processing with the segmentation method (Növoa et al. 2008). Correlation is widely used as an effective similarity measure in matching tasks. Matching two uncalibrated images with large camera motion such as significant rotation and scale changes still remains a difficult problem (Zhao, Huang, and Gao 2006).

Correlation coefficient (CC) is a common tool to highlight the variations, and it helps in similarity measurement. CC gauges the resemblance between two images. It is used to expound the quality of a least squares fitting of the sequence of images (Vaduva et al. 2013).

A well-known process in the spatial domain is block matching, where a set of pixels is represented by a block in the current frame is compared, based on a suitable matching criterion, with pixels in the reference frame. The mathematical calculation in the block matching process is intensive and limiting the motion vector between two adjacent frames leads to searching for a match within a smaller window than the image frame (Ahmed, Hussain, and Al-Jumeily 2011).

Motion estimation (ME) plays a key role in achieving efficient video compression in devices such as digital video camera, digital TV, portable storage, mobile cameras and video conferencing. The block matching algorithm for ME has been widely adopted in many video compression standards, because it is effective at decreasing temporal redundancy and simple to implement. In the algorithm, the current frame is first divided into macroblocks (MBs), which are fixed-sized square blocks, and the motion vector (MV) for each MB is estimated by finding the closest block of pixels within its search range in a reference frame according to some matching criteria. The sum of absolute difference (SAD) is often used as a matching criterion between the current macro-block and the candidate blocks because of its lower complexity compared with other matching criteria such as the sum of squared difference (SSD) or the mean square error (MSE) (Jin, Lee, and Jeong 2008).

In the context of medical images, a combination of lossless and lossy techniques has been applied to angiogram images. As there were regions with no vessels present, preserving all of the details of such regions would not be diagnostically useful. Hence, these could be removed or encoded in a lossy manner. For regions where arteries were present, lossless encoding was applied. Firstly, all frames are partitioned into non-overlapping blocks. The blocks are categorized into region of interest (ROI) and non-ROI ones, by applying an edge detection algorithm. Some of the blocks are removed using the temporal correlation among the non-ROI blocks of consecutive frames. Different prediction methods were used for the ROI and Non-ROI blocks based on the different characteristics of these blocks. Seven contexts based on the intensity and importance of each block were identified. Applying thses contexts to all of the blocks of a sequence took advantage of context modeling. In the final step, every context was coded with adaptive Arithmetic Coding (Yazdi et al. 2010).

Huffman Coding (HC) is a variable length coding that specifies longer codes to symbols with lower probabilities and shorter bit codes to symbols with higher possibilities. This coding scheme is effective in compressing differential data (Song and Shimamoto 2007). The Run-Length Encoding (RLE) is one of the most well-known and simplest methods applied to encode iterative data or code pattern in a single code (Nunez and Jones 2003).

The combination of these two efficient compression methods, RLE and HC, was proposed to decrease the data volume, pattern delivery time, and economize power in scan applications (Nourani and Tehranipour 2005). In medical images, the combination of RLE and HC has been implemented on X-ray angiograms and MRI images to fulfil maximum compression (Shyam Sunder, Eswaran, and Srirama 2005). The same combination of RLE and HC was executed on color images after quantization and thresholding, enabling the Discrete Wavelet Transform (DWT) coefficients to gain a better result in (Setia and Kumar 2012).

In our recent work, we performed lossless compression of Fluoroscopy medical images using correlation and HC (Arif, Mansor, Logeswaran, et al. 2012). The proposed method achieved an average compression ratio of 7.97. We then extended the work to include the combination of HC and RLE. Specifically, a new framework for lossless medical image compression based on classification of the images by correlation and coding the differences between the sequential images using the combination of RLE-HC, was proposed. The extended method attained an improved average compression ratio of 11.41 (Arif, Mansor, Abdul Karim, et al. 2012). The work was further extended by extracting the ROI of each image, calculating the correlation coefficient (CC) to
examine image similarity, identifying the ROI difference, and then only applying the RLE-HC combination method (R.Huff-Seg.) to gain further improvement in compression. The extended method attained significantly improved compression ratio of 29.73 (Sameh Arif et al. 2013).

The main contribution in this paper is to further improve the compression performance without adversely affecting the diagnostic quality of the Fluoroscopy images, by adapting the previous techniques with two main contributions. The first contribution is dividing the difference matrix into blocks and applying the RLE on those blocks (Adaptive RLE). The second contribution is to undertake range conversion in representing the coded images. To the best of our knowledge, there are no other published works employing this technique in the context of medical image compression.

**Region Coding and Correlation:**

Determining and eliciting a precise region coding is the essential step before coding and compressing the image data for efficient storage or transmission. By analyzing various spatial regions and determining the RC of the image, it is possible to compress it into different levels of reconstruction quality. Images can be classified into two regions: (1) Region Coding (RC), (2) Background Region Coding (BRC). This way, one could properly preserve the features necessary for medical diagnosis or scientific measurement, while realizing higher overall compression by allowing retrogression of data in the inconsequential regions (Arif, Mansor, Logeswaran, et al. 2012).

The correlation is specified by the variance and co-variance, where the variance is measured for a dimension within itself, while the covariance is measured between two dimensions. The formulae for the calculation of variance (Var) and co-variance (Cov) are given as follows (Arif, Mansor, Abdul Karim, et al. 2012; Sameh Arif et al. 2013):

\[ \text{Var}(X) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n-1} \]  
\[ \text{Var}(Y) = \frac{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}{n-1} \]  
\[ \text{Cov}(X,Y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{n-1} \]

\[ R_{xy} = \frac{\text{Cov}(X,Y)}{\text{Var}(X)\text{Var}(Y)} \]  

To calculate the correspondence between the original image and the reconstructed image, the correlation coefficient (CC) is calculated as follows:

\[ \text{CC} = \frac{\sum_{x,y} f(x,y) \overline{f(x,y)} - \overline{f(x,y)} \overline{f(x,y)}}{\left( \sum_{x,y} f(x,y)^2 \right)^{1/2} \left( \sum_{x,y} \overline{f(x,y)}^2 \right)^{1/2}} \]

where \( x = \{0, 1, 2, \ldots, M-1\}, y = \{0, 1, 2, \ldots, N-1\}, \overline{w} \) is the average value of the pixels in \( w \), \( \overline{f} \) is the average value of \( f \) (intensity function) in the region coincident with the current location of \( w \), the summations are taken over the coordinates common to both \( f \) and \( w \), and \( M \times N \) is the size of the original image. The CC is scaled within the range (-1 to 1), independent of scale changes in the amplitude of \( f \) and \( w \) (Arif et al. 2014; Bharti, Gupta, and Bhatia 2009).

**Methodology:**

The proposed framework can be divided into five main stages: Classification, Segmentation, Block Reduction, Encoding and Range Conversion as shown in Fig. 1. The process is reversed to remodel the series of images upon decompression. The three main stages, i.e. Classification, Segmentation and Encoding, have been clearly described in previous works (Arif, Mansor, Abdul Karim, et al. 2012; Sameh Arif et al. 2013).

There are three major regions in the fluoroscopy image, as shown in Fig. 2: black area, white area and Region of Coding (RC). The diagnostically pertinent information is contained in the third region that constitutes the (RC), shown in Fig. 3. The images are first classified into sets based on general similarity. Then, the RC of all images is extracted, as shown in Fig 4.
Fig. 1: Proposed framework.

Fig. 2: Important areas in Fluoroscopy images.

Fig. 3: Important areas in Region Coding (RC) Fluoroscopy images.

(a) Original Image
(b) Segmented Image

Fig. 4: Set of Pharynx and Esophagus Fluoroscopy images taken from the same view.

**Block Reduction:**

The difference between images is calculated by subtracting the second (test) image from the first (reference) image. That subtraction between the two similar images (RCs) generates a large number of zero values in all parts of the output matrix except areas corresponding to liquid motion. This work divides the resultant N×N subtraction matrix into a number of n×n blocks, most of which are similar with zero values as shown in Fig 5. Thus, a modified form of RLE (i.e. Adaptive RLE) is proposed, which searches for sequential similar blocks instead of searching for singular pixel values. The output of Adaptive RLE is the number of similar blocks and the compressed form of the block itself, as shown in Fig 6. The size of the divided blocks affects the performance of the proposed technique; large blocks reduce time and search cost but increase the probability of containing different details (i.e. lower probability of finding similar blocks). Small size results in
many similar blocks, but they tend to behave as ordinary RLE. Depending on the output characteristic of the subtraction matrix, it was found that the $8 \times 8$ block yields the premium compression ratio, as compared to blocks of sizes $4 \times 4$, $16 \times 16$ and $32 \times 32$ pixels. The $8 \times 8$ block is compared with successive blocks. Once a non-similar block is found, the number of similar blocks before the different one, and the compressed form of the non-similar block are be saved. The non-similar block will be considered the new reference block and the process continues. Finally, the result is further encoded using the HC technique.

**Fig. 5:** RC Block Reduction.

**Fig. 6:** RC $8 \times 8$ matrix division.

**Range Conversion:**

In this step, the number of bits used to represent the image is reduced by transforming image value ranges. The new pixel value ($X_{new}$) is determined using the equation below:

$$X_{new} = \frac{X_{old} - Min}{Max - Min} \times R + Start$$

(6)

where, $X_{old}$ is the old value of the pixel, $Max$ and $Min$ are the maximum and minimum values of the old range, $R$ is the new range and $Start$ is the beginning value of $R$.

The main novelty in this approach is to use the above equation to constrain the range of (0-255) values to a new narrower range that can be represented by less number of bits, hence a smaller file size and higher compression ratio. The equation was applied four times on the sets of images. In each time, the range reduction was changed, and the PSNR was calculated to evaluate the quality of the output images.

The bit reduction arising from the range reduction is depicted by Fig. 7. The corresponding improvement in compression performance achieved is shown in Table 1.

**Table 1:** Demonstrate the bit reduction for each matrix, the range of values that convert it to it and the compression ratio (CR) improvement in each case of bit reduction.

<table>
<thead>
<tr>
<th>Bit reduction</th>
<th>Range</th>
<th>CR improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Bit</td>
<td>0-127</td>
<td>CR×1.143</td>
</tr>
<tr>
<td>2 Bits</td>
<td>0-63</td>
<td>CR×1.33</td>
</tr>
<tr>
<td>3 Bits</td>
<td>0-31</td>
<td>CR×1.6</td>
</tr>
<tr>
<td>4 Bits</td>
<td>0-15</td>
<td>CR×2</td>
</tr>
<tr>
<td>5 Bits</td>
<td>0-7</td>
<td>CR×2.66</td>
</tr>
</tbody>
</table>
RESULTS AND DISCUSSION

Experiments were performed on 386 greyscale clinical fluoroscopy images obtained from Serdang Hospital, Malaysia to evaluate the validity of the proposed approach. Each image was of dimension 512×512 pixels and file size of 256 KB. The performance evaluation, in terms of compression ratio (CR), is calculated as follows:

\[
CR = \frac{S_o}{S_d} \tag{7}
\]

where, \(S_o\) = file size of the original image, 
\(S_d\) = file size of the difference image.

Higher correlation corresponds to a higher similarity, resulting in a higher CR. From Table 2, it is also observed that the proposed method (RC-Block Reduction) achieved significantly better performance than implementing RLE-HC on the region of interest (R. Huff–ROI) of the difference images, the RLE-HC on difference images (R. Huff-Diff.) and also the standard lossless combination (R. Huff) compression of the images. For example, in the case of images 005 and 006, R. Huff only produced a CR of 1.38, while R. Huff-Diff. realized a CR of 11.41, and R. Huff-Seg. achieved a CR of 12.21. However, the proposed RC-Block Reduction implemented based on the CC indications managed to achieve a CR of 35.94 for the RC-Block reduction. For a diagnostically lossless that approach (RC-Block reduction and Range conversion) achieved 71.88 of CR.

**Table 2:** Comparison of compression ratio performance (CR) and related correlation coefficient (CC) values of the various techniques for two sets of images.

<table>
<thead>
<tr>
<th>Ref Image</th>
<th>Test Image</th>
<th>CC</th>
<th>Compression Ratio (CR)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>R. Huff</td>
</tr>
<tr>
<td>330005</td>
<td>330006</td>
<td>0.93</td>
<td>1.38</td>
</tr>
<tr>
<td>330004</td>
<td>330005</td>
<td>0.95</td>
<td>1.34</td>
</tr>
<tr>
<td>330009</td>
<td>330010</td>
<td>0.95</td>
<td>1.36</td>
</tr>
<tr>
<td>330007</td>
<td>330008</td>
<td>0.95</td>
<td>1.36</td>
</tr>
<tr>
<td>330010</td>
<td>330011</td>
<td>0.95</td>
<td>1.35</td>
</tr>
<tr>
<td>330006</td>
<td>330007</td>
<td>0.95</td>
<td>1.36</td>
</tr>
<tr>
<td>330012</td>
<td>330013</td>
<td>0.98</td>
<td>1.35</td>
</tr>
<tr>
<td>011004</td>
<td>011005</td>
<td>0.86</td>
<td>1.33</td>
</tr>
<tr>
<td>011008</td>
<td>011009</td>
<td>0.94</td>
<td>1.32</td>
</tr>
<tr>
<td>011005</td>
<td>011006</td>
<td>0.88</td>
<td>1.33</td>
</tr>
<tr>
<td>011012</td>
<td>011013</td>
<td>0.98</td>
<td>1.35</td>
</tr>
<tr>
<td>011011</td>
<td>011012</td>
<td>0.95</td>
<td>1.37</td>
</tr>
<tr>
<td>011006</td>
<td>011007</td>
<td>0.95</td>
<td>1.34</td>
</tr>
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<td>011007</td>
<td>011008</td>
<td>0.97</td>
<td>1.35</td>
</tr>
<tr>
<td>011013</td>
<td>011014</td>
<td>0.97</td>
<td>1.36</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
<td>1.35</td>
</tr>
</tbody>
</table>

Fig. 7: Bit Reduction.
Table 3 shows the average CR achieved across the sets of test images for the various methods. It is clear that the proposed method significantly improved the compression performance. Further analysis of the results is given in Table 3, where the results obtained for two sets of images are given, along with the corresponding correlation coefficient values.

**Table 3:** Comparison of average compression ratio performance between the proposed method (RC-Block Reduction) on the difference segmented images, as compared to the implementation of the combination of RLE and HC on the standard images (R. Huff), on the difference images (R. Huff-Diff), and on the ROI difference images (R. Huff-Seg.), for a random sample of ten images.

<table>
<thead>
<tr>
<th>Group No.</th>
<th>No. of Images</th>
<th>Average Compression Ratio (ACR)</th>
<th>R. Huff</th>
<th>R. Huff-Diff</th>
<th>R. Huff-Seg.</th>
<th>RC-Block Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>011</td>
<td>13</td>
<td>1.35</td>
<td>8.22</td>
<td>16.15</td>
<td>71.43</td>
<td></td>
</tr>
<tr>
<td>330</td>
<td>19</td>
<td>1.31</td>
<td>9.85</td>
<td>18.83</td>
<td>83.28</td>
<td></td>
</tr>
<tr>
<td>954</td>
<td>25</td>
<td>1.34</td>
<td>5.85</td>
<td>18.76</td>
<td>61.48</td>
<td></td>
</tr>
</tbody>
</table>

In Fig. 8 and Fig. 9, the performance is plotted against the block sizes used. It is shown that the level of achieved CR is dependent on the number of blocks used in block reduction. The highest CR is achieved for the 8×8 block size, with compression performance dropping to the lowest for the block size of 32×32. This is due to the fact that the larger the block, the probability of similarity matching of the entire block is reduced. The performance of the 4×4 block size was not the highest as very small blocks require the image to be segmented into many blocks, thus the overheads incurred in coding the numerous blocks compromises the gains in similarity. As such, the optimum block size identified in this experiment was 8×8.

![Fig. 8](image-url) Evaluate the Performance of RC Block Reduction for different sizes (Set 011).

![Fig. 9](image-url) Evaluate the Performance of RC Block Reduction for different sizes (Set 330).

Results based only on CR when loss of quality is incurred, is inadequate as a very high CR could be achieved due to significant loss of information in the image. The quality performance of the proposed
framework for medical image compression in this work was evaluated using two measures, objective and subjective. Both measures complement each other. The objective measure calculated using PSNR (Peak Signal to Noise Ratio) gives the scientific numerical calculation of the error between the reconstructed and the original image. However, as diagnosis is routinely done visually by medical experts, the subjective evaluation of the diagnostic quality interpretation via the human visual system and experience of medical experts has to also be taken into account. This was undertaken by a double-blind test where radiologists were asked to identify the the reconstructed image in a set of images. A second subjective test was conducted where the original and reconstructed images were displayed and the radiologists were asked to indicate the level of difference observed in a MOS (Mean Opinion Score) test.

53 random clinical Fluoroscopy images were tested using the objective and subjective measures. In the first subjective test, it was found that up to 91% were unable to recognize the reconstructed images in a set of corresponding original images. The results achieved for the PSNR and MOS tests for the five block reduction options of one bit to five bits reduction (as conducted in (Akhtar et al. 2008)) are given in Table 4. From the table, it is observed that as expected, as the number of bits used to represent the data decreases, the PSNR decreases. However, from the MOS results, it is observed that even with a 4-bit reduction (i.e. only using 4 bits to encode the range 0-15), the medical specialists found that the reconstructed images were diagnostically indistinguishable from the original.

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR (0-127)</th>
<th>MOS</th>
<th>PSNR (0-63)</th>
<th>MOS</th>
<th>PSNR (0-31)</th>
<th>MOS</th>
<th>PSNR (0-15)</th>
<th>MOS</th>
<th>PSNR (0-7)</th>
<th>MOS</th>
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</thead>
<tbody>
<tr>
<td>4-5</td>
<td>74.97</td>
<td>5</td>
<td>69.43</td>
<td>5</td>
<td>50.86</td>
<td>5</td>
<td>45.41</td>
<td>5</td>
<td>24.16</td>
<td>5</td>
</tr>
<tr>
<td>8-9</td>
<td>75.43</td>
<td>5</td>
<td>69.99</td>
<td>5</td>
<td>49.96</td>
<td>5</td>
<td>44.61</td>
<td>5</td>
<td>23.73</td>
<td>5</td>
</tr>
<tr>
<td>5-6</td>
<td>75.51</td>
<td>5</td>
<td>69.96</td>
<td>5</td>
<td>50.92</td>
<td>5</td>
<td>45.46</td>
<td>5</td>
<td>24.18</td>
<td>5</td>
</tr>
<tr>
<td>12-13</td>
<td>77.64</td>
<td>5</td>
<td>72.17</td>
<td>5</td>
<td>50.23</td>
<td>5</td>
<td>44.85</td>
<td>5</td>
<td>23.86</td>
<td>5</td>
</tr>
<tr>
<td>11-12</td>
<td>77.25</td>
<td>5</td>
<td>71.77</td>
<td>5</td>
<td>50.27</td>
<td>5</td>
<td>44.88</td>
<td>5</td>
<td>23.88</td>
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</tr>
<tr>
<td>6-7</td>
<td>75.48</td>
<td>5</td>
<td>69.97</td>
<td>5</td>
<td>50.59</td>
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<td>45.17</td>
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<td>24.03</td>
<td>5</td>
</tr>
<tr>
<td>7-8</td>
<td>76.42</td>
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<td>70.88</td>
<td>5</td>
<td>50.92</td>
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<td>45.46</td>
<td>5</td>
<td>24.18</td>
<td>5</td>
</tr>
<tr>
<td>10-11</td>
<td>77.01</td>
<td>5</td>
<td>71.52</td>
<td>5</td>
<td>50.41</td>
<td>5</td>
<td>45.01</td>
<td>5</td>
<td>23.94</td>
<td>5</td>
</tr>
<tr>
<td>13-14</td>
<td>78.16</td>
<td>5</td>
<td>72.68</td>
<td>5</td>
<td>50.28</td>
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<td>44.89</td>
<td>5</td>
<td>23.88</td>
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</tr>
<tr>
<td>14-15</td>
<td>79.76</td>
<td>5</td>
<td>74.2</td>
<td>5</td>
<td>51.01</td>
<td>5</td>
<td>45.55</td>
<td>5</td>
<td>24.23</td>
<td>5</td>
</tr>
<tr>
<td>15-16</td>
<td>80.09</td>
<td>5</td>
<td>74.54</td>
<td>5</td>
<td>50.93</td>
<td>5</td>
<td>45.48</td>
<td>5</td>
<td>24.19</td>
<td>5</td>
</tr>
</tbody>
</table>

**Conclusion:**

In this paper, a new framework for lossless and diagnostically lossless image compression for groups of images based on the adaptive RLE-HC combination has been proposed. The technique concentrates on the RC to code the difference between the groups of images using adaptive RLE and the combination of RLE and HC. The method implemented on pharynx and esophagus fluoroscopy images has been shown in this work to be able to achieve significant improvement in compression performance of up to almost 500%. In addition, the block reduction method employed further improved the CR achieved to 157.26 without any distinguishable loss in diagnostic quality even with a 4 bit reduction. It is expected that the proposed framework would work for other types of medical and non-medical images as well.

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