Near-lossless image compression using an improved edge adaptive hierarchical interpolation

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ABSTRACT

Lossy image compression of medical images is required to store efficiently a huge amount of medical data on a remote storage device and to reduce transmission time of the image across a low-bandwidth communication. On the other hand, lossless compression of medical images is recommended because the loss of minor information leads to wrong medical diagnosis results that affects the life of patients. To compromise the conflicting requirements of lossy and lossless image compression methods, a near-lossless image compression method is proposed. In the previous work, an edge adaptive hierarchical interpolation (EAHINT) algorithm was proposed for progressive lossless image compression. In this paper, EAHINT algorithm was enhanced for scalable near-lossless image compression. The proposed interpolation algorithm has three linear components, namely, one-directional, multi-directional and non-directional linear interpolators. The EAHINT algorithm switches adaptively among the three linear interpolators based on the strength of the edge in a local context of the current pixel being predicted. The strength of the edge in local window was estimated using the variance of the pixels in the local window. Although the actual predictors are still linear functions, the switching mechanism tried to deal with non-linear structures like edges. Simulation results demonstrate that the improved interpolation algorithm has better compression ratio over the original EAHINT algorithm and JPEG-Ls image compression standard.

1. INTRODUCTION

In image compression, high priority has been given for compression ratio criteria. In line with this, the compression performance of a multi-resolution (hierarchical) image compression method is lower than the compression performance of a single resolution (non-hierarchical) image compression method. As a result of this, multi-resolution form of image compression has not been very popular for lossless applications [1-3]. However, progressive image transmission mode of multi-resolution image encoding scheme is required when the size of the image data over a slow link is very large. Pyramid algorithms such as hierarchical interpolation (HINT) [4], interleaved hierarchical interpolation (IHINT) [5] and new interleaved hierarchical interpolation (NIHINT) [6] have been shown to be superior among hierarchical form of lossless image compression techniques in medical imaging.

In these pyramid algorithms, the predictor coefficients are constant for all input images as well as for all levels of the pyramid in the same input image. Since these algorithms are based on space-invariance model, they fail to capture the fast changing statistics around edges. To address this problem, edge adaptive hierarchical interpolation (EAHINT) scheme was developed [7, 8]. In this paper, EAHINT is improved by
improving the down sampling method of the image. Experimental results demonstrate that the new image down sampling method improves the compression ratio of interpolation errors of the images over the original EAHINT algorithm and JPEG-LS image compression standard.

The rest of the paper is organized as follows. In section 2, a review of lossy, lossless and near-lossless mode of image compression algorithms is given. In section 3, an overview of the improved edge adaptive hierarchical interpolation (I-EAHINT) for progressive near-lossless image encoding is described. In section 4, each components of the I-EAHINT scheme is described. The experimental results are presented in section 5. Finally, the conclusions are derived in section 6.

2. REVIEW OF LOSSY, LOSSLESS AND NEAR-LOSSLESS COMPRESSION METHODS

Spatially adaptive linear interpolation techniques have been proposed for lossy image compression by means of least-squares optimization [9-15]. They are effective for an arbitrary edge direction. However, finding the optimal coefficients is computationally very expensive because the least-squares covariance matrix is computed for each pixel from its large size local window. Hence, the use of these complex algorithms is limited to develop fast and real-time image transmission systems. To address this problem, a number of simple pyramid data structures have been developed for lossless multi-resolution image coding schemes, namely, the hierarchical INTerpolation (HINT) [4], the interleaved hierarchical INTerpolation (IHINT) [5], the new interleaved hierarchical INTerpolation (NIHINT) [6], edge adaptive hierarchical INTerpolation (EAHINT) [7] and other hierarchical image compression methods [16, 17]. The weakness of HINT, IHINT and NIHINT prediction algorithms is explained in detail in [7].

Generally, these interpolative algorithms do not use techniques to identify the directions of strong intensity correlations near the target pixel so as to exploit the directional correlations among neighboring pixels. As a result of this, interpolation errors along sharp edges are large and cannot be encoded efficiently by entropy coders. To address the weakness of these interpolation methods, Edge Adaptive Hierarchical INTerpolation (EAHINT) was developed [7]. Based on the local variance of the casual context of the current pixel, the EAHINT algorithm has three statistical decision rules to classify the strength of the local edge into strong, weak, or medium.

By definition, in near-lossless image compression, the value of any pixel of a decompressed image is not changed in magnitude by more than $\sigma$-gray level value when it is compared with the original gray level value. Assume a gray level image with $R$ number of rows and $C$ number of columns is denoted by a 2-dimensional array of integer values $I(i,j)$, where $0 \leq i < R$ and $0 \leq j < C$. Assume that the decompressed version of the image $I$ is denoted by $\tilde{I}(i,j)$. Based on these two assumptions, the purpose of $\sigma$-level near-lossless image compression is to obtain a decompressed (approximation) image $\tilde{I}(i,j)$ which satisfies the following equation.

$$
\|x\|_e = \text{MAX}|I(i,j) - \tilde{I}(i,j)| \leq \sigma, \tag{1}
$$

where $\sigma$ is the level of error tolerance. In this paper, the value of $\sigma$ is 1. Hence, near-lossless image compression has been proposed as trade-off between low compression ratio of lossless image compression algorithm and high distortion of lossy image compression algorithm [18-23].

3. OVERVIEW OF THE IMPROVED EAHINT FOR NEAR-LOSSLESS COMPRESSION

The improved EAHINT algorithm and the original EAHINT are different significantly in the information of the low sub-band component of the hierarchical representation of the image. However, both methods use similar prediction context to interpolate the current pixel. In both methods, the value of the current pixel $c$ is interpolated by determining the strength and direction of the local edge as shown in Figure 1.

![Figure 1. A 3x3 rectangular window of neighboring pixels to predict the current pixel C](image-url)
The variance ($\sigma^2$) of the causal neighbors of the current pixel $c$ is used to estimate the activity level of the prediction context. Using the value of the local variance, the local area can be classified as an edge area or a smooth area. Hence, the predictor switches between a non-directional linear interpolator for a smooth area and a one-directional interpolator for an edge area. A multi-directional interpolator is also used as a compromise between the two extreme edge strengths. Based on Figure 1, the pseudo code of the main components of the EAHINT algorithm is given as follows.

The Pseudo Code of EAHINT Algorithm to Interpolate Central Pixel C

1. Let $P = (P_1, P_2, P_3, P_4, P_5, P_6, P_7, P_8)$ be a local vector from a 3x3 local window as shown in Figure 1.
2. Set two threshold values: $T_1$ and $T_2$
3. Calculate variance $\delta$ of the local window ($P$)
4. if ($\delta^2 > T_2$)
   5.   \{ 
   6.     Compute mean $\bar{x}$ of local window ($P$)
   7.     if $P_i \leq \bar{x}$
   8.       Assign $P_i$ to Group 1, where $i = 1, 2, 3, 4, 6, 7, 8$, and 9
   9.   \}\ else 
10.   Assign $P_i$ to Group 2, where $i = 1, 2, 3, 4, 6, 7, 8$, and 9
11. Compute $\delta_1^2$ and $\delta_2^2$ for each group
12. if ($\delta^2 > \delta_1^2 + \delta_2^2$)
13.   Go to line 19.
14. \} \ else if ($T_1 < \delta^2 \leq T_2$)
15.   Go to line 20.
16. \} \ else 
17.   Go to line 21.
18. One-Directional Linear Interpolator ($P$) as shown in [7]
19. Multi-directional Adaptive Weighing Linear Interpolator ($P$) as shown in [7]
20. Non-directional Static Weighing Linear Interpolator ($P$) as shown in [7].

Since the weight along one particular direction is dominant in the presence of a strong edge, interpolation is performed only along that particular direction. Since the weights are almost equivalent in the presence of weak edges (smooth regions), static weighing linear interpolation is used. For edges with medium strength, multi-directional adaptive weighing linear interpolator is used as a compromise between the two extreme types of edges. The formation of the low sub-band image using an improved image down sampling method is described in detail in the following section.

4. DETAILED DESCRIPTION OF IMPROVED EAHINT ALGORITHM

Assume the original image $I$ is represented as a two dimensional array $I[R, C]$ where $R$ is the number of rows and $C$ is the number of columns of the original image $I$. The existing EAHINT algorithm for progressive lossless image compression is improved by generating low subband component of the original image using new image down sampling method. Both algorithms scan the original image three times to encode and transmit the image progressively. Figure 2 and Figure 3 shows a 3x3 shaded region as a casual context to interpolate the central pixel in the first three passes of the original EAHINT algorithm and its improved version, respectively. The difference between the original EAHINT algorithm and the improved EAHINT algorithm is described in detail in the following three sub-sections.

4.1. Formation and Extrapolation of a Low Sub-band Image

In the first pass of the original EAHINT algorithm [7], the low subband of an image is generated by simply sampling even-row and even-column indices $I(2i, 2j)$ from the original image $I$ as shown in Figure 2(a). These pixels can be denoted by $L_1(i, j) = I(2i, 2j)$, where $0 \leq i < R/2$ and $0 \leq j < C/2$. The dimension of this sub-sampled image is $I[R/2, C/2]$. The subscript to $L$ determines the stage of the scan of the original image. By using several scanning stages of the original image, a hierarchical pyramid data structure can be generated. However, in this paper, the input image is scanned three times to generate two hierachical resolutions of the original image.
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From equation (2), the value of $S[i,j]$ can be even or odd. If the value of $S(i,j)$ is even, there is no truncation error in the creation of the pixel $L_t(i,j)$ when $S(i,j)$ is divided by 2. However, if the value of $S(i,j)$ is odd, there is a truncation error in the creation of the pixel $L_t(i,j)$ when $S(i,j)$ is divided by 2. This implies that 1-bit is lost among 8-bits of the original image due to truncation error. Hence, according to the definition of near-lossless image compression, the value of $\sigma$ is 1 ($\sigma = 1$). Due to this reason, the improved EAHINT algorithm can be called near-lossless hierarchical image compression. Note that when both $I(2i,2j)$ and $I(2i+1,2j+1)$ diagonal pixels are even, their sum $S(i,j)$ is even. Moreover, when both $I(2i,2j)$ and $I(2i+1,2j+1)$ diagonal pixels are odd, their sum $S(i,j)$ is even. However, when one of diagonal pixels is odd and the other is even, their sum $S(i,j)$ is odd. If we consider the variable $S(i,j)$ as a uniform random variable, the probability of the random variable $S(i,j)$ to be even is $2/3$ and its probability to be odd is $1/3$. Mathematically, $P(S(i,j)=\text{even})=2/3$ and $P(S(i,j)=\text{odd})=1/3$. Hence, only one-third of the total number of pixels in a low subband image can have truncation error. However, for near-lossless image compression with $\sigma=1$, each pixel has a truncation error of 1-bit. This implies that the improved EAHINT is not fully near-lossless image compression in comparison to the full near-lossless image compression with $\sigma=1$.

4.2. Formation and Interpolation of High Subband (H2) Pixels of an Image

In the second pass of the original EAHINT algorithm, high subband (H2) pixels with odd-row and odd-column indices $I[2i+1,2j+1]$ are encoded for $0 \leq i < R/2$ and $0 \leq j < C/2$ as shown in Figure 2(c). There are 8-connected neighboring pixels to interpolate the central pixel as shown in Figure 2(c). Among these 8-connected neighboring pixels, the 4-connected pixels are not available directly during the first pass as well as from the upper and left neighbours of the second pass itself and they are indicated by question mark (?) as shown in Figure 2(c). They are estimated from the average of a pair of vertical or horizontal adjacent pixels of the current pixel before computing the variance of the 3x3 local window as shown in [7].

On the other hand, in the second pass of the improved EAHINT algorithm, pixels with even-row and even-column indices $I(2i,2j)$ as well as pixels with odd-row and odd-column indices $I(2i+1,2j+1)$ are encoded at the same time by interleaving each other as shown in Figure 4, where $H_2$ denotes a pixel with index $I(2i,2j)$ and $h_2$ denotes the corresponding diagonal pixel with index $I(2i+1,2j+1)$. Practically, the encoder module does not encode $h_2$ pixels with index $I(2i+1,2j+1)$ because the decoder module can extract $h_2$ pixels from equation(2) using the following equation.

$$h_2 = I(2i+1,2j+1) - I(2i,2j) = 2L_t(i,j) - H_2$$

(3)

where, $0 \leq i < R/2$ and $0 \leq j < C/2$. Similar to the original EAHINT, among the 8-connected casual predictor pixels of the central pixel, only the 4 pixels which are located at the diagonal direction of the central pixel are available directly. The remaining 4 pixels which are in the horizontal and vertical directions of the central pixel are not available directly. These missed pixels can be estimated by taking the average of its pair of adjacent pixels in the horizontal or vertical direction before computing the variance of local window.

![Figure 4](image-url)  
Figure 4. A 3x3 casual prediction context for pixels in the second pass. a) Causal context of a pixel value at I (4, 4) as an example to illustrate context of H2 pixels. b) Casual context of any H2 and d h2 pixel types, where $H_2 = I(2i,2j)$ and $h_2 = I(2i+1,2j+1)$. Note that the $h_2$ pixels with red color in the improved EAHINT algorithm is different from the value of $H_2$ pixel types in the original EAHINT algorithm. In Figure 4(b), the $h_2$ pixels represent the value in low subband image. In other words, the value of $h_2$ pixels cannot be extracted by decoder because the decoder did not know the current central H2 pixel, where $H_2 = I(2i,2j)$. 

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4.3. Formation and Interpolation of High Subband (H₃) Pixels of an Image

In the third pass of the original EAHINT algorithm, high subband (H₃) pixels with even-row and odd-column indices I[2i, 2j + 1] as well as odd-row and even-column indices I[2i + 1, 2j] are encoded by interlacing each other as shown in Figure 2(d). To predict pixels with index I [2i, 2j + 1] or I(2i + 1, 2j), among 8-connected neighbouring pixels, only 2 neighbouring pixels are not available directly to the central pixel. These neighbouring pixels are not available from the first pass, second pass as well as from the upper and left neighbours of the third pass itself. These two pixels can be computed from its four available pixels as shown in [7]. Similar to the original EAHINT algorithm, in the third pass of the improved EAHINT algorithm, high subband (H₃) pixels with even-row and odd-column indices I[2i, 2j + 1] as well as odd-row and even-column indices I[2i + 1, 2j] are encoded by interlacing each other as shown in Figure 5. Pixels with index I [2i, 2j + 1] or I(2i + 1, 2j) are predicted similar to the pixels in the original EAHINT algorithm.

![Location of H₂ pixels in the image](image)

**Figure 5.** A 3x3 causal prediction in the third pass; a) causal context of the pixel I (2, 3) as an example of H₃ pixels (high-band pixels). b) Causal context of any H₃ pixel types, H₃ = I (2i, 2j+1) or H₃ = (2i+1, 2j)

5. RESULTS AND DISCUSSION

In this section, we evaluate the performance of the improved EAHINT (I-EAHINT) algorithm for progressive near-lossless image compression in comparison to the original algorithm EAHINT (O-EAHINT) for progressive lossless image compression. It is also compared with the JPEG-LS standard [24]. Six common standard test images with 8 bits per pixel and size of 512x512 are used in our experiments as shown in Figure 6. The comparison of the compression ratio of the improved EAHINT algorithm with the original EAHINT and the JPEG-LS is presented in Table 1. The compression ratio is obtained by dividing the total number of bytes of the input image before compression by the total number of bytes after compression. Therefore, the more the compression ratio, the better the performance of the encoder algorithm. For all test images, the improved EAHINT method performs better than the other two methods. On average, the improved EAHINT algorithm improves the compression ratio of the original EAHINT algorithm by 2.73%. It also improves the compression ratio of JPEG-LS algorithm by 1.75%. The performance of the improved EAHINT algorithms increases as the number of layers of the hierarchical image representation increases from two layers into three more layers. Moreover, the performance of the improved EAHINT algorithms increases by adding context adaptive error correction model as shown in [8].

The compression ratio of the improved EAHINT method is better than the compression ratio of the other two methods because of the following two reasons. The first reason is that in the first pass of the original EAHINT algorithm, low subband pixels are far apart by one pixel with each other due to image down sampling without using low-pass filtering as shown in Figure 2(a). This implies that since image down sampling in an edge area introduces uncertainty about the direction and exact location of the edge in the original image, a large interpolation error will be created if the interpolation is done across sharp edges instead of doing...
along the direction of the sharp edge. The second reason for the better performance of the improved EAHINT algorithm is the presence of data redundancy in the low subband image. Since a pair of adjacent diagonal pixels are highly correlated in the original image, the accuracy of the prediction of the current pixel increases. This implies that the subband image can be compressed easily.

Figure 6. Images used for the experimental evaluation of the improved EAHINT Algorithm

Table 1. Comparison of the compression ratio of the improved EAHINT algorithm with the original EAHINT algorithm and JPEG-LS standard

| Image     | EAHINT | JPEG-LS | IEAHINT |
|-----------|--------|---------|---------|
| Baboon    | 1.32   | 1.33    | 1.34    |
| Boat      | 1.65   | 1.67    | 1.68    |
| Lena      | 1.90   | 1.89    | 1.95    |
| Pepper    | 1.76   | 1.78    | 1.80    |
| sailboat  | 1.58   | 1.61    | 1.61    |
| women     | 1.95   | 1.94    | 2.01    |
| Average   | 1.69   | 1.70    | 1.73    |

6. CONCLUSION

In this paper, a near-lossless progressive image compression is developed by improving the low subband image formation method of the original EAHINT algorithm. The low band image formation is improved by using a diagonal of two adjacent pixels as a simple form of a low-pass filter. This operation increases the correlation among the neighbouring pixels in the low subband image. This, in turn, makes the prediction errors in the low subband images to be encoded efficiently. The improved algorithm uses the correlation among neighbouring pixels to extract higher order local image structures such as texture, edge and corner in a better way by using circular context. Since two-third of the total number of pixels in the low band image have no truncation error, the improved EAHINT algorithm is not fully near-lossless. Hence, the improved algorithm balances the trade-off between fully lossless and fully near-lossless for medical image applications.

To model the non-linearity of the image structure, a nonlinear method for hierarchical image interpolation is used. Based on the strength of local edge, the interpolator switches among three linear interpolators. Since only the causal contexts are used in the encoder, no additional side information needs to be transmitted to the decoder and the decoder also has the same interpolator as the encoder.

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