REGION-SPECIFIC WAVELET COMPRESSION FOR 4K SURVEILLANCE IMAGES

ANKUSH RAI*, JAGADEESH KANNAN R

School of Computing Science & Engineering, VIT University, Chennai, Tamil Nadu, India. Email: ankushressci@gmail.com

ABSTRACT

For successful transmission of massively sequenced images during 4K surveillance operations, a large amount of data transfer cost high bandwidth, latency, and delay of information transfer. Thus, there lies a need for real-time compression of this image sequences. In this study, we present a region-specific approach for wavelet-based image compression to enable management of huge chunks of information flow by transforming Harr wavelets in hierarchical order.

Keywords: Wavelet compression, Region-specific compression, Multi-resolution.

INTRODUCTION

Wavelets are mathematical tool that enables the hierarchical decomposition of functions because of which it has gain high popularity in image compression. Although there are several lossy compression schemes that have been proposed in the past studies, the wavelet transformation-based image compression schemes remain the most familiar one among the fellow researchers and have achieved several industrial applications [1]. The advantage of this approach is that irrespective of high compression ratios, it provides better picture enhancement and ensures the integrity of the image quality. It has already been established lossy compression method due to its characteristics to handle discontinuous data and gives higher peak signal to noise ratio values [2,3].

In the lossy compression scheme, the actual signal of the reconstructed data cannot be exactly recovered but can be approximated to it with a high level of resemblance [4]. The reason behind this is that much of its detail from the original signal is discarded while ensuring that the appearance of the signal vastly remains the same. For illustration, consider a scenario where the image of an object occupies several megabytes of the disk space [5]. After the application of lossy compression the minute details of the image will be discarded but overall the image size is greatly reduced [6]. This is useful in several of the areas such as television broadcasting, video conferencing, and information transmission where certain amount of errors is admissible in trade of increased bandwidth. Such methods include Fractal compression, transform coding, Fourier-related transformation, discrete cosine transformation, and wavelet transformation [7-9]. In other compression schemes, such a lossless compression scheme the exact replica of the original data can be created. This is familiarly known as entropy encoding. It does not necessarily fetches high compression in data size and isnot truly useful in image compression scenario. It has wide applications in compression of legal or medical records. Such methods include entropy encoding, Huffman coding, Bit-plane coding, run-length coding, and Lempel–Ziv–Welch coding [10]. In this study, we propose a lossy compression scheme for image compression and compare the compressed data with the parameters such as peak signal to noise ratio, structural content, normalized absolute error to test the integrity, and preseverance of imagery quality.

METHODS

We employ the multiwavelet transformation to break down the given image to be compressed into a pyramid of features which is linked to one another in a logical manner. This will allow us to perform tree-based searching and allocation for a given color scheme which will be independent from feature decomposition for both high- and low-resolution image [11]. Therefore, the image can be broken into wavelets using the following functions as given below

$$f(x,y) = \frac{1}{\sqrt{MN}} \sum_m \sum_n W_\phi(j_o,m,n)\phi_{j_o,m,n}(x,y) +$$
$$\frac{1}{\sqrt{MN}} \sum_m \sum_n W_\psi^i(j,m,n)\psi_{j,m,n}^i(x,y)$$

Where the indices j_o, j, m, n are the non-negative integers, x and y are the pixels position at point P, M, and N are the real valued tensor coefficients, ϕ is the scaling function, and ψ is the wavelet function in corresponding scaling and wavelet function is given by W_ϕ, W_ψ^i. The scaling coefficients from the given noisy image are at different resolution in a mammogram while the wavelet coefficients from the feature vector in the noise retrieval step; that the reason why different types of scanners are used in recording the mammogram which in turn is dependent on the optical density.

Here, the sequence of coefficients of a one-dimensional image is represented in the form of vector space V. Therefore, a one-pixel image can be represented as the function of a piece-wise constant over the interval [0.1). Thereby, for all such functions comprising an image is a subset of V. This allows us to write a two-pixel image over the interval [0.1/2) to [1/2.1). On continuing this pattern, the traversal of the whole image can be summed into 2^j equal subintervals for V^j vector subspaces. Hence, the scaling functions of the wavelets can be written as

$$\phi_j^i(x) = f(2^j - i) \quad i = 0,1,2\ldots 2^j - 1$$

$$\phi(x) = \begin{cases} 1 \text{ for } 0 \le x < 1 \\ 0 \text{ otherwise} \end{cases}$$

Thereby, the wavelet coefficients are given by

$$\psi_j^i(x) = \psi(2^j x - i) \quad i = 0,1,2\ldots 2^j - 1$$

$$\psi(x) = \begin{cases} 1 \text{ for } 0 \le x < 1/2 \\ -1 \text{ for } 1/2 \le x < 1 \\ 0 \text{ otherwise} \end{cases}$$
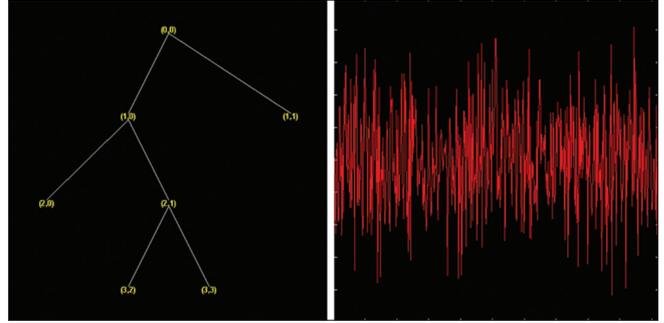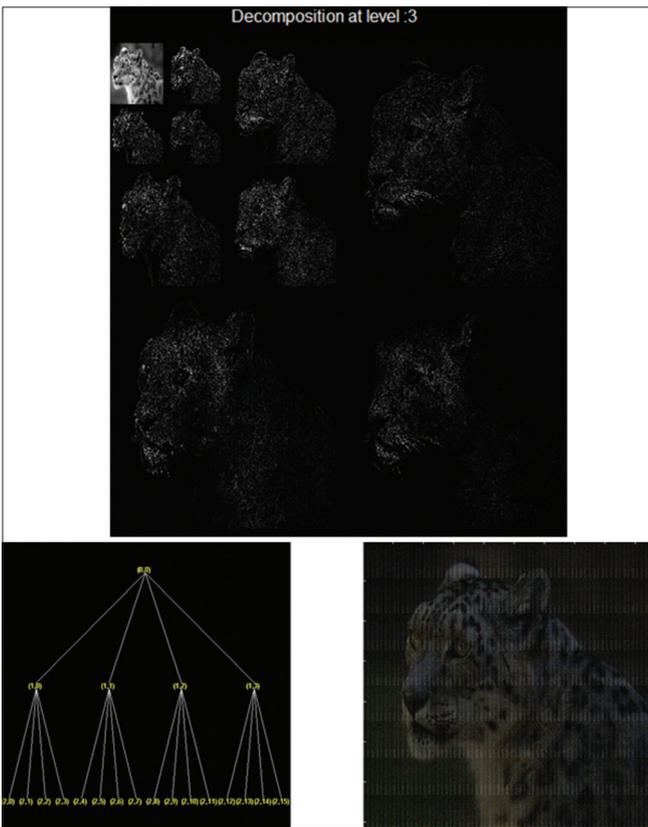
Fig. 1: Read input image I

Fig. 2: Illustration of the decomposition of wavelets in the form of logical manner using the above equation

This allows us to get the 2D signal for the discrete wavelet transformation from 1D signals by multiplying the two 1D functions, that is, $\phi(x,y) = \phi(x)*\phi(x)$ [12]. There exist three functions of wavelet corresponding to the scan details of vertical, horizontal, and diagonal directions, given as,

$$\psi^{(1)}(x,y) = \phi(x)\psi(y) \ //\text{horizontal}$$

$$\psi^{(2)}(x,y) = \psi(x)\phi(y) \ //\text{vertical}$$

$$\psi^{(3)}(x,y) = \psi(x)\psi(y) \ //\text{diagonal}$$

Now, we need to model the filter bank for each of its sub-band to facilitate the compression of the redundant data of the decomposed input image using

Fig. 3: Illustration of the formation of non-redundant features

Fig. 4: Output denoised image I

the following equations (Fig. 2). Let the so derived 2D matrix in previous steps be represented as X and w be the weights of the corresponding columns of the matrix X; such that the reduction in redundancy data (Fig. 3) for the image to be compressed can be written as:

$$\{T_i, R_i\} = \arg\min(\|w\| + \rho\|X - R*w\|_m^2)$$

$$T_i = \frac{\left(X*w^T_i\right)}{\left(w_i*w^T_i\right)}$$

$$R_{i+1} = \left(\int_I \left|T_i(x-1,y-1) - T_i(x+1,y+1)\right| dx\right)^{1/2}$$

Where, T_i and R_i are the target indices for the output of the compressed image and R_i is the redundant column array for the weight vectors (w) needed to decompress the image, ρ is the compression ratio to regularize parametric stability of the compressing process, m is the mean of the diagonal pixels in the current window size of 4×4, 8×8, and 16×16, R_{i+1} helps in predicting the redundancy in the consequent iterations of the processing, I is the image with m×n rows and columns; output figure is shown in Fig. 4. The emphasis is toward parsing the redundant information with the weight matrices to define its significance of association with the decomposed wavelet features [13]. The flow chart of the work flow process involving the compression process is given in Fig. 5.

Algorithm: Region-specific wavelet compression algorithm (RSWCA)

Input: Image I with m × n arrays.
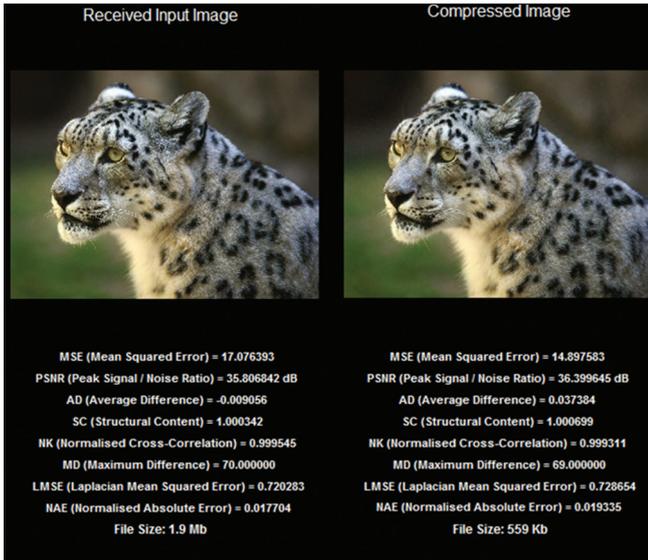
Output: Compressed image I'

Fig. 5: Compraission of the image properties of the input image and that of output image when processed through the presented region-specific wavelet compression algorithm
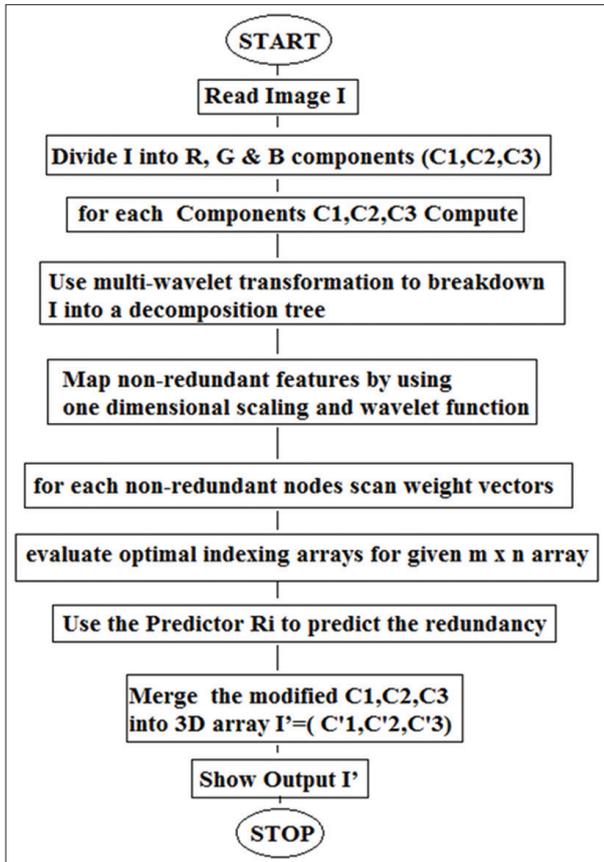

Fig. 7: Sample results of the compression of high contrast images using region-specific wavelet compression algorithm

Fig. 6: Flow chart of the region-specific wavelet compression algorithm

Step 1: Divide the arrays of the read image into R, G, and B components (C_1, C_2, C_3) of size m × n.

Step 2: For each components C_1, C_2, C_3 compute

Step 3: Use multiwavelet transformation to break down the given image into a pyramid of features which is linked to one another in a logical manner. Therefore, the decomposition tree is given as
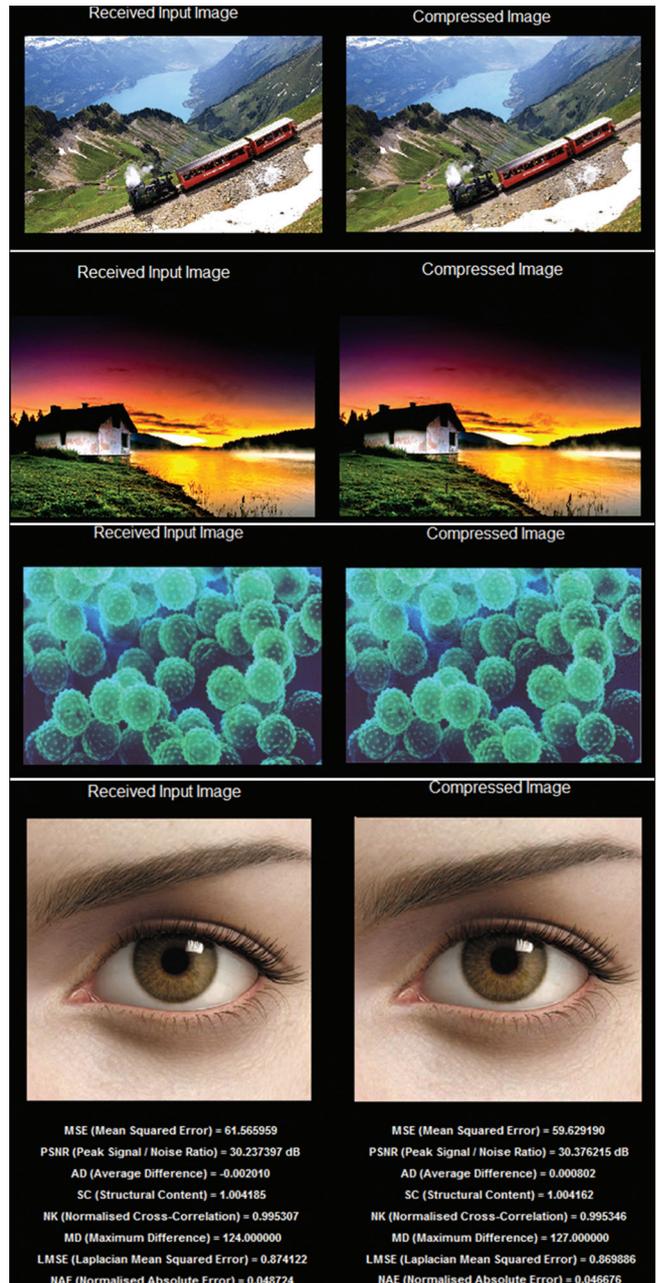
$$f(x,y) = \frac{1}{\sqrt{MN}} \sum_m \sum_n W_\phi(j_o, m, n) \phi_{j_o, m, n}(x, y) + \frac{1}{\sqrt{MN}} \sum_m \sum_n W_\psi^i(j, m, n) \psi_{j, m, n}^i(x, y)$$

Step 4: Map the unique non-redundant features from the given image using one-dimensional scaling and wavelet function

$$\phi_j^i(x) = \phi(2^j - i) \quad i = 0, 1, 2 \ldots 2^j - 1$$

$$\psi_j^i(x) = \psi(2^j x - i) \quad i = 0, 1, 2 \ldots 2^j - 1$$

Step 5: For each non-redundant nodes (x, y) scan weight vectors and evaluate optimal indexing arrays for given m x n array

Table 1: Compression results of test images showing preseverance of image integrity and quality

Image instances of Fig. 1	Patch window size	Given test image		Compressed image	
	Even sized	MSE	SNR	MSE	SNR
1	4×4	0.00099669	27.4244	0.0018087	29.2572
2	4×4	0.00098415	25.3041	0.0016533	28.8478
3	4×4	0.00098072	28.9817	0.003711	30.8989
4	4×4	0.0010013	25.7159	0.00037186	31.3495
5	8×8	0.00074276	23.2035	0.00013993	28.3495
6	8×8	0.00083882	20.886	0.00010589	29.9232
7	8×8	0.00088107	18.7317	0.00016077	25.9367
8	16×16	0.0009948	15.7691	5.7354e-05	28.778
9	16×16	0.00098492	21.494	0.00019801	28.6501
10	16×16	0.00089379	16.2776	0.0032242	23.9822

MSE: Mean square error, SNR: Signal to noise ratio

$$\{T_i, R_i\} = \arg\min(\|w\| + \rho\|X - R * w\|_m^2)$$

Step 6: Predict the redundancy by evaluating

$$R_{i+1} = \left(\int_I |T_i(x-1, y-1) - T_i(x+1, y+1)| dx \right)^{1/2}$$

Step 7: End for

Step 8: End loop for C_1, C_2, C_3.

Step 9: Update color nodes at x, y by merging C_1, C_2, C_3 into 3D array I'=(C'_1, C'_2, C'_3), show output I'

Step 10: End process.

CONCLUSION

We have presented the quantifying success of the proposed algorithm for compressing the digital images with high contrast (Fig. 6). Table 1 represents the performance range of compression for the test image shown in Fig. 1 with different patch window size for computation and its influence represented in form of mean square error and SNR are the two standard parameters used to compare the performance of compression. The assessment of comparative performance results for the denoizing methods with that of the RSWCA algorithm suggest the affectivity of performance for the proposed method (Fig. 7). The quality compression is achieved without elimination of the features and contrast-based imagery data. The future prospect of the algorithm will allow us to implement the proposed compression scheme with the other learning-based algorithms like that of a neural network or fuzzy algorithm to achieve better stats of compression.

REFERENCES

1. Bhavani S, Thanushkodi K. A survey on coding algorithms in medical image compression. Int J Comput Sci Eng 2010;2(5):1429-34.
2. Kharate GK, Pati VH. Color image compression based on wavelet packet best tree. Int J Comput Sci 2010;7(3):31-5.
3. Haque MR, Ahmed F. Image Data Compression with JPEG and JPEG 2000. 8th International Conference on Computer and Information Technology; 2005. p. 1064-9.
4. Weinberger MJ, Seroussi G, Sapiro G. The LOCO-I lossless image compression algorithm: Principles and standardization into JPEG-LS. IEEE Trans Image Process 2000;2:1309-24.
5. Joshi MA. Digital Image Processing: An Algorithmic Approach. New Delhi: PHI; 2006. p. 175-217.
6. Rahman CM, Saber AY. Image Compression using Dynamic Clustering and Neural Network. 5th International Conference on Computer and Information Technology, December; 2002. p. 453-8.
7. Koli NA, Ali MS. A survey on fractal image compression key issues. Inf Technol J 2008;7(8):1085-95.
8. Bottou L, Howard PG, Bengio Y. The Z-coder Adaptive Binary Coder. In: Proceeding of IEEE DCC, March; 1998. p. 13-22.
9. Khalifa O. Wavelet coding design for image data compression. Int Arab J Inf Technol 2009;6(2):118-27.
10. Blessie AA, Nalini J, Ramesh SC. Image compression using wavelet transform based on the lifting scheme and its implementation. IJCSI Int J Comput Sci 2011;8(3):449.
11. Rai A. Attribute based level adaptive thresholding algorithm (ablata) for image compression and transmission. J Math Comput Sci 2014;12:211-8.
12. Rai A. A comorbid algorithm to significantly compress text contents of several web pages in conformational dynamics. J Multimed Technol Recent Adv 2014;1(2):1-3.
13. Rai A. Shell implementation of neural net over the UNIX environment for file management: A step towards automated operating system. J Oper Syst Dev Trends 2014;1(2):10-4.