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Image Compression Process Using Fractional Fourier Transform and Wavelets Techniques

Faris Sattar Hadi

Information Technology Research and Development Center, University of KUFA, Iraq

Corresponding Author: Fariss.alkaabi@uokufa.edu.iq

Abstract: Compression process is very important for data transfer in information technology. The difficult part of the data compression process is keeping quality of data transferred at high compression ratio. In this research we introduce a new image compression process that uses both fractional Fourier transform and wavelet. While wavelets are the best method for feature extraction from the image, the low frequency of wavelet decomposition are the part in compression process that most of the present methods don't touch it. On the other hand, fractional Fourier transform is a suitable and helps in the compressed coding of the image. Hence, we have used fractional Fourier transform to compress sub-bands of the wavelet. In this technique, an image is divided into low frequency and high frequency sub bands by using (Daubechies wavelet filter) and level one quantization for both low frequency and high frequency sub bands. The low-frequency sub bands are compressed by using Fourier transform with optimal fractional solution, and high-frequency sub bands are compressed by removing zeroes and storage only non-zero blocks and its position. The compressed wavelet coefficients are compressed by applied of level two quantization and kept as array. This array is programmed by using arithmetic encoder and followed by run length programing. The experimental results of the proposed technique with a different testing image are compared with some of the existing image compression techniques. The results show that the proposed technique has un important enhancement in reconstruction of image quality.

Keywords: Image compression. Quantization. Sub bands. One dimensional discrete fractional Fourier transform (DFrFT).

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1. Introduction

The image compression process in the past has developed the field of data communication. In these days high-definition photograph editing, live video stream and multimedia messages are easy and fast because of compression process [1, 2]. The compression process services in representing the original image with a smaller number of bits. Time frequency-based compression techniques have the property of multi scale description, which gives high quality of image rebuilding [3–5]. Popular compression technique JPEG 2000 [6] practices discrete wavelet transform that splits the image as tiles in small number. The wavelet transform is applied to each tile independently to improve the quality of the reconstructed original image. However, the growth in the number of tiles leads to aliasing result [7, 8], which is a limitation of this process. Discrete fractional Fourier transform (DFrFT) is a simple programing process which explains the characteristics of signals, step by step by varying them from a time domain to the frequency domain as 0 to 1. The fractional part in DFrFT delivers the additional degree of freedom in calculations of coefficient values and also helps in a compact programing of information with the smaller number of discrete Fourier transform (DFT) coefficient values [9].

Some compression procedures [10–12] use wavelets, and a lossless image compression technique [13] uses a mixture of wavelet transform and particular value decomposition to return a good resolution in image reconstruction quality. A mixture of wavelet with a discrete transform (DT) [14] displays an increase in compression performance with a big computational time.

This research is planned as follows: First: explains the usage of wavelet transform and DFT in image compression. Second: offerings a proposed image compression process. The final results and examination are discussed.

2. Discrete wavelet transform and Fourier transform

2.1 Discrete wavelet transform

The multi resolution structures of wavelet transform offer the graded set of scaling and wavelet functions to appear an original signal with less number of frequency tasters. For each decomposition level, it makes two classes of wavelet coefficient values (approximate and detailed) [15, 16]. In two dimensional wavelet decomposition, for each level, it products approximate, horizontal detail, vertical detail and diagonal detail sub bands shown in Fig(1).

In wavelet decomposition process, for each level of decomposition, wavelet coefficient values are decimated by a factor two, which services in reaching good compression ratio. In wavelet decomposition, low frequency wavelet coefficient values are spread towards top left corner and high frequency detailed coefficient values are spread to the bottom right corner. As decomposition level rises, the detailed coefficient values are developed by less important wavelet coefficient values for the reconstruction procedure, and by ignoring the very first level of detailed coefficient values may yield the highest compression ratio [17].

Daubechies (Db) mother wavelet is the most generally used wavelet in an image compression process, as is orthogonal wavelets of compact sustenance. The (Db) wavelets used meeting window function, and the decomposed wavelet coefficient values emulate all variants between pixel intensities, which are useful in the programing of important coefficient values for image compression process.

The Daubechies 5 mother wavelet, which is used in this proposed work, has five wavelet and scaling coefficient values [18].

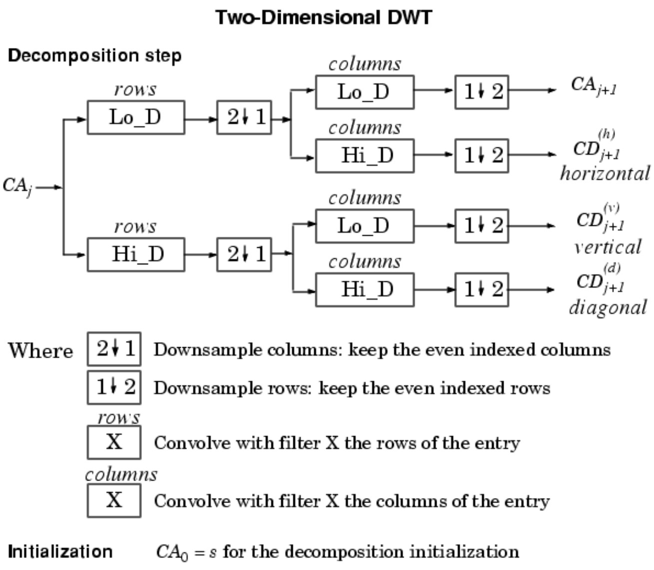

Figure 1. Wavelet decomposition coefficients for the first level

2.2. Discrete fractional Fourier transform

The growth of continuous fractional Fourier transforms for signal examination made many scientists to develop a discrete part for it. There are some approaches to calculate the matrix of this technique. Time constraint through computational method is desirable [19]. This technique defined in [20] practices a set of vectors of the Discrete Fourier transform matrix as a complement to the Hermite Gaussian function which look likes this technique.

3. Methods

This study improves the compression performance by utilizing the best transform features. The low-frequency (LL) and high-frequency (non-LL) sub bands of a source image can be utilized to extract the spectrum using the wavelet transform. The following lists the steps that make up the suggested technique shown in Figure 2.

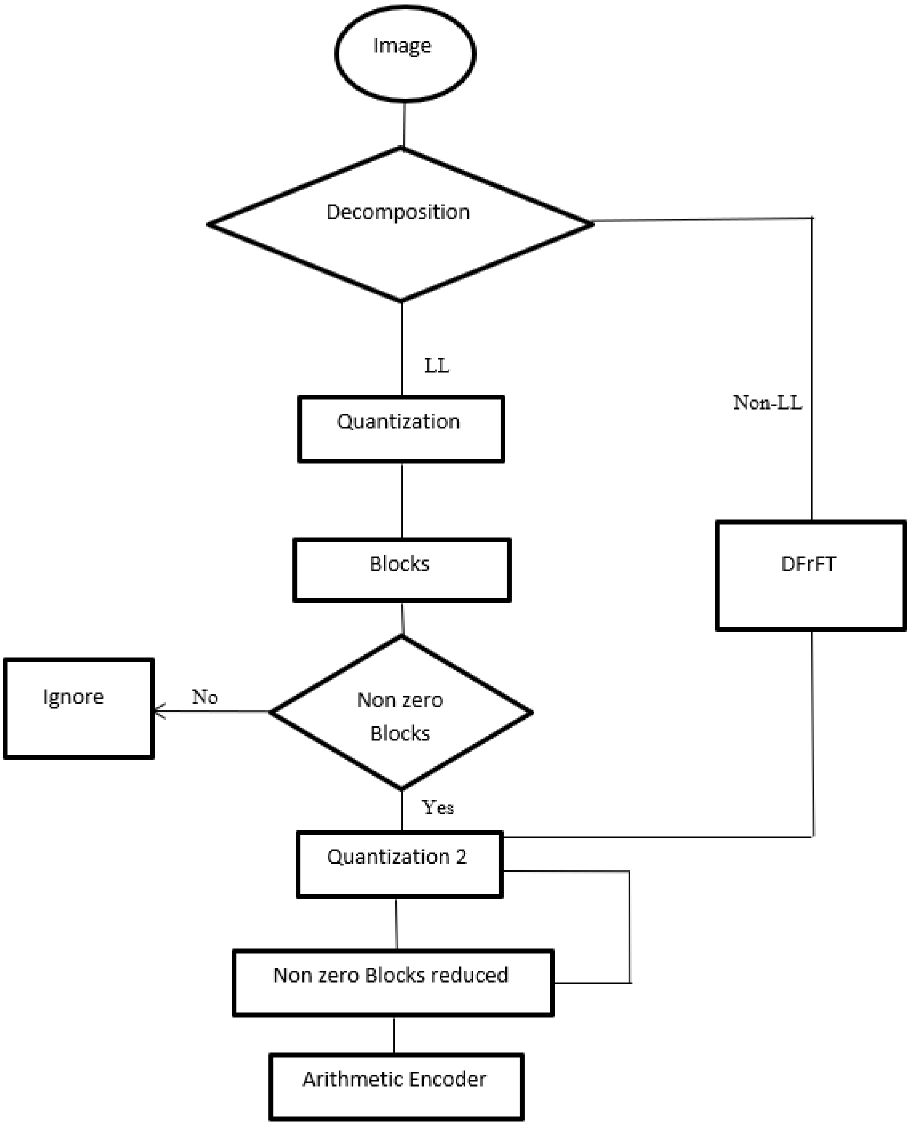

Figure 2. Block view of a proposed method

First Step To begin, determine the dimensions of a test image and use the mother wavelet Daubechies of scale 5 for the two-dimensional discrete wavelet transform for decomposition. There are LL and non-LL sub-bands in the source image. Step 2: To improve the correlation, apply level 1 quantization to the decomposed subbands.

It is the product of the quantized sub-band (either LL or non-LL) median value and the defined quantization scale* (0.01 for LL and 0.1 for non-LL). By dividing the decomposed sub-bands by the factor, the new quantized sub-band. Quantization scale 0.01 denotes a division of 1% by the median value in the LL sub-band by all of the values in the LL sub-band. Since non-LL subbands require coarse quantization and are less significant, they are given a large quantization scale. Step Three LL sub-band coding In the level 1 quantized LL sub-band, one-dimensional DFrFT with the optimal fractional order (opt) is applied to every column. Coefficients are organized into two-dimensional arrays following DFrFT compression. Level 2 quantization is then applied to the transformed matrix in order to divide the values. Step 4: Non-LL sub-band coding Quantized non-LL sub-bands at Level 1 are divided into standard-sized non-overlapped blocks, such as 4 × 4, 8 x 8, and so on. Make a regular 4-by-4 window and slide it up to the end of the sub-band and left to right. If a nonzero value is discovered in the block, both its position and value will be kept.

Zero-numbered blocks are ignored and not kept. For nonzero blocks, use quantization level 2 and save the results as a reduced array.

Step 5: Since reduced arrays are encoded using an arithmetic encoder and contain both positive and negative values, they are all encoded into a compressed bitstream. In order to eliminate encoding values that recur frequently, this encoding strategy also uses a run-length encoder (RLE).

Step Six The arithmetic decoder decodes decreased arrays during the decompression phase, which is the opposite of the compression process. The level 2 quantization factor and inverse DFrFT with fractional order were used to retrieve the LL sub-bands. In a similar vein, non-LL sub-bands moved back to their initial positions, and any leftover blocks were padded with zero. To rebuild the original image, multiply the quantization factor for each non-LL sub-band once more and use an inverse discrete wavelet transform.

4. Results and discussions

We have selected original test photos with a standard resolution, such as an a house, boat, aerial, peppers and Barbara to assess our compression algorithm. Two optimization techniques are used by this algorithm to improve the performance of lossless compression.

1. Choosing an appropriate mother wavelet The decomposition process of this approach makes use of "Daubechies" tap-5 (DB-5) mother wavelet filters. With the set of quadrature mirror filters, its five vanishing moments are sufficient to eliminate the non-significant wavelet coefficients.

2. Fractional order optimization This approach compresses the LL sub-band using a one-dimensional DFrFT kernel with optimal fractional order. Because of their strong correlation, the wavelet coefficients in LL sub-bands require particular fractional orders to be compressed. As a result, fractional orders are computed by hand, and one particular value is chosen to yield the maximum CP. We compute the best fractional orders using the LL sub-bands of the images for discussion's sake. for LL and non-LL sub-bands) will not alter the information.

The compression algorithm is put into practice and assessed as follows by utilizing all of the aforementioned optimization techniques: The PRD and PSNR values of the suggested approach at high compression percentages, ranging from 50% to 100%, are tabulated in together with the ideal fractional orders for the image. Fractional orders ranging from 0.94 to 0.99 are used to lower the PRD and raise the PSNR values. For both the decomposed wavelet coefficients and the original picture compression. The wavelet coefficients in LL sub-bands exhibit high correlation, making it challenging to distinguish between significant and non-significant coefficients.

Even with significant loss in the reconstructed image, the PSNR value is still high. By calculating the pixel-to-pixel error between the original and reconstructed images, however, measuring PRD is helpful for refining this technique as lossless compression.

5. Conclusion

In this paper, a lossless image compression technique based on a one-dimensional DFrFT and two-dimensional DWT combination is introduced. The algorithm's efficiency is increased by using wavelet decomposition to extract sub-bands at various frequencies and by using DFrFT to compactly code the low-frequency sub-band. The proposed method operates efficiently at high compression percentage, despite its limitations, which include the decoder's dependence on the encoded bitstream and the reconstruction of the original image using fractional orders ranging from 0.80 to 0.99. These limitations are demonstrated by the results and a comparative study with other algorithms. The reconstruction quality is higher with this compression ratio as well, which may be advantageous for applications involving the compression of multimedia images.

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