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AN IMPROVED VLSI ARCHITECTURE USING WAVELET FILTER BANK FOR BLUR IMAGE APPLICATIONS

Kabilan R.[1], Ravi R.[2], Jenniefer J. Sherine R.[1], Rajakumar G.[3] and Mini Minar V. C.[1]
[1]Department of ECE, Francis Xavier Engineering College, Tirunelveli, Tamilnadu, India
[2]Department of IT, Francis Xavier Engineering College, Tirunelveli, Tamilnadu, India
[3]Francis Xavier Engineering College, Tirunelveli, Tamilnadu, India
E-Mail: rkabilan13@gmail.com

ABSTRACT

An effective image compression technique using 2D-Discrete Wavelet Transform (DWT) is proposed. It has been implemented using a 6-tap Daubechies filter bank for providing reduced adder count and path delay. The proposed architecture first acquires feature points by local binary pattern (LBP). Then, they are encoded by wavelet filter bank and blur noise is removed from the image. The algebraic integer (AI) technique provides a simple representation for the irrational basis coefficients of the transform. This compressed image is reconstructed using inverse feature transform. The compression performance (CP), objectively peak signal to noise ratio and subjectively visual quality of image are measured and it is found that they outperform the existing method. The proposed method can be used in medical imaging.

Keywords: image, VLSI, DWT, DAUB-6, LBP, MSE, PSNR, CP.

INTRODUCTION

In our day to day daily life, sharing and storing of data (e.g.:-texts, audio, images, videos) has become a basic task. If the data is shared or stored without losing their originality in less amount of space, then it is called data compression. One among them is image compression. Image compression decreases the number of extraneous and similar data in the image. Scalability, region of interest coding, Meta information and processing power are some of the properties of image processing.

Lossless and lossy compressions are the two kinds of image compression technology. The lossless compression constructs an image similar to the original image. But the lossy compression is favoured often as their compression ratio is notably high, despite the fact of discarding similar data. This is also called as visually lossless.

Transform coding [4] is a class of lossy compression. It has techniques like the Discrete Fourier Transform (DFT), Discrete Cosine Transform (DCT), Discrete Haar Transform (DHT), and Walsh Transform that is homologous to Fourier transform. Discrete wavelet transform (DWT) is a progressing technique in the current scenario. DWT [7] is the platform for JPEG-2000 standard of image coding. They are used highly in digital image compression, de-noising, medical and scientific applications. DWT has a disintegrating and multi-resolution ability. Among, a wide range of wavelets, the proposed architecture is restricted to Daubechies 6 filter bank. Their members ranges from highly localized to highly smooth.

Lifting based architecture is used to design the daub6 2DDWT. It is the combination of both the high pass and low pass filters. Therefore, a DAUB6 2DDWT is proposed using lifting based architecture. Here, Local Binary Pattern is also used in addition for binary conversion of image pixel values for efficiency. The PSNR, MSE and the comparison ratio are calculated using the simulation results and are displayed in the Matlab command widow. Finally, the speed, delay, number of adders and power are also calculated.

The remaining parts of the paper unravels as problems reviews about the problems prevailing in the existing systems, problem solution describes the architecture of DAUB 6 2DDWT filter bank and results and discussion shows the simulation results. The paper is concluded and the future works are presented in conclusion and future scope.

PROBLEMS

Quadtree Decomposition, Discrete Cosine Transform and Haar Wavelet Transform are some of the prevalent methods. They are also used in the image compression technique for applications like medicine and scientific approaches. Still they have some problems like blocking artifacts, utilizing large amount of space, less efficient de-noising property and difficult to achieve preferred results for complex images.

Quadtree decomposition

Quadtree decomposition is a type of lossy compression. Over an ample range of rates, it can compress the digital image data. Therefore, complete evaluation of high resolution areas and Meta information searching can be attained. Quadtree decomposition [6], an abstract type structure, cleaves into different block sizes of an image. Later quantization takes place by any preferred algorithm. Here, decomposition of four quadrants of an image block takes place by conserving the nearby blocks spatial characteristics. Each block is coded by a geometrical tile of two polynomial pieces divided by linear discontinuity. They use binary formats only. It deals with blocking artifacts, which prevent them from attaining good fidelity even at low rates. This causes blurring effect which is not advisable.

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Most of their cells have same resolution which makes it difficult to differentiate. They are shift sensitive as the spatial requirements depend on their origin position. As they utilize large space, a limit is needed to be imposed to the level of division for storage or process time or for the resolution of the response.

Discrete cosine transform

DCT expresses a sequence of finite numerous data points. It is expressed in terms of a sum of cosine functions oscillating at different frequencies, which is widely used in image compression. In order to get good de-correlation they exploit the inter pixel redundancies of the natural images. It transforms an image from spatial domain to the frequency domain. They use fixed point values and have an excellent energy compaction. First, division of small N*N blocks of the whole image takes place and then application of DCT are done on each of these blocks. After that for minimizing the storage space of DCT coefficients, they are quantized. It is done through dividing by quantization matrix, which is a lossy process. So selection of quantization value or quantization matrix affects the entropy and compression ratio. In this decoding process, we have to keep N's value same as it used in encoding process. Then we do de-quantization process by multiplying with quantization value or quantization matrix. Output image is not exact copy of original image but it is same as original image as the less important frequencies are discarded. So, DCT [5] has block artifacts. Then the remaining frequencies are used to retrieve the image in decomposition process. As a result, reconstructed image is distorted. It provides inappropriate results for non-high frequency complex images.

Haar wavelet transform

The numerical solution from the nonlinear differential equations of fractional order is obtained by Haar wavelet transforms. The Haar Wavelet Transformation [1] is a simple form of compression such that the resulting matrix is similar to the initial matrix which involves the process of averaging and subtracting terms, saving detail coefficients, banishing data, and matrix restoration. It is represented as an orthonormal function basis. HWT is not continuous hence it is not a differentiable one. First, the inputs weighted average for n/2 rows is taken for two at a time. Basic vectors are sequencly ordered and they map integers to the irrational numbers. They have poor energy compaction for images and low computing requirements. Without the help of a temporary array memory efficiency can be calculated.

While generating next level average values and set of coefficients, the Haar transform performs an average and subtract operation on a pair of values. Then the algorithm over by two values it shifts and calculates another average and subtraction operation on another next pair. All the high frequency changes of the high frequency coefficient spectrum should be reflected. The Haar window is of two elements range and if a big change takes place from an even number value to an odd number value, the change will not be calculated in the high frequency coefficients. The Haar wavelet's de-noising property is also not always so effective, since the transform can't compress the energy of the original signal into a few high-energy values lying above the noise threshold. Therefore, some drawbacks are present in the Haar wavelet transform.

PROBLEM SOLUTION

The solution of the above stated problem considers a coloured blur image. It is converted into a gray-scale image of specific size. The Feature transform, wavelet filter bank and inverse feature transform are applied to the pixel values. Then from the compressed image the original image is reconstructed. The MSE and PSNR values are calculated by comparing the original and reconstructed image. The process flow takes place as per the flow chart in Figure-1.

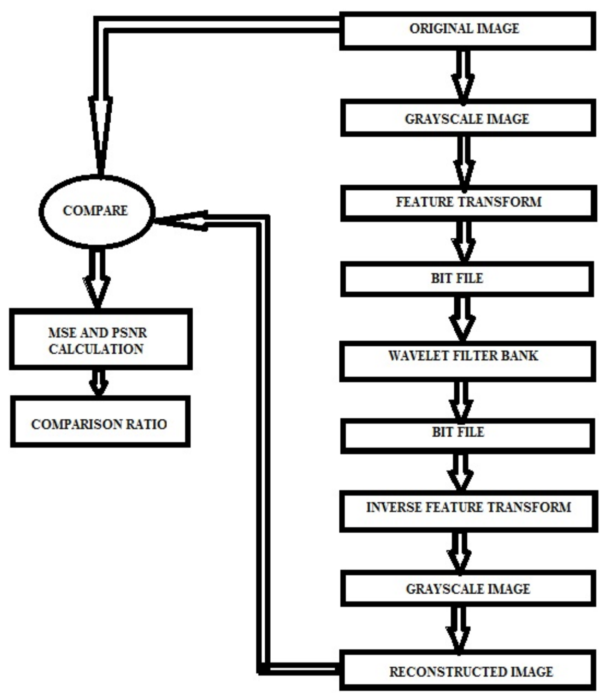

Figure-1. The block diagram of the proposed architecture.

Image initialization

A blur image is considered as the input. It is of any image format including JPEG, TIFF, GIFF and PNG. As the images captured by the digital cameras or from the personnel digital assistant (PDA) or mobile phones which incorporate the digi-cam may produce blur. Gaussian blur, motion blur, bokeh, defocus aberration and box blur are some types of blur. They occur due to the pictures, that are captured while in motion or from a quite long distance etc... Therefore, the distortion level of the pixel value against the frequency it occurs called the histogram, is calculated and equalized.

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Then, the size of the image is estimated. As VLSI, uses only fixed values; the image size is fixed to [256, 256]. If the selected image exceeds the fixed value, it is reduced to the specified range. Also it is converted into single sample image. The pixel values obtained from the selected image as integers are arranged in a matrix format.

Feature transform

The feature transformation is used for capturing the nonlinearity. They stabilize the variances in the pixel values. One among them is the local binary pattern [3]. Local binary pattern are used to tag the image pixels by thresholding their neighbourhood values. Here, the method of tagging is done by considering nearby image pixels of range $\theta = 0° - 360°$ i.e. in the shape of a circle and then replacing them by binary values. The procedure is as follows:

- The window is divided into 3*3 cells.
- For each pixel value 'eight' neighbhour pixel values circled around the central pixel are compared.
- If the value of a nearby pixel is greater than the central pixel then replace it by value a '1' else replace it by a '0'.
- Repeat the above step for all the pixel values.
- Finally, equalize the histogram obtained.

The Feature transform encompasses a Feature function that computes the projections of an image along specified directions of x' axis and y' axis by,

$$R_\theta(x') = \int_{-\infty}^{\infty} f\,(x' \cos\theta - y' \sin\theta, x' \sin\theta + y' \cos\theta)\, dy \quad (1)$$

Here,

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} cos\theta & sin\theta \\ -sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \qquad (2)$$

The Feature points are obtained by applying Feature transform using Feature functions.

Bit file

It is a format for storing of bit-stream for individual FPGA family to support partial reconfiguration. Here, the binary values obtained from the above step are stored in a txt. file. Then they are called in the filter architecture for wavelet filter process.

Wavelet filter bank

It is an array of band pass filters. It is composed of both discrete wavelet transform and inverse discrete wavelet transform. Wavelets have best energy compaction capability for highly correlated images. Daubechies 6 tap filter architecture [2] has been used here. It is used for providing reduced adder count and path delay. The AI-based algorithm to compute the Daubechies Wavelet Transform is intended to be used in applications where the quality of restoratio of the image is crucial. Due to the error-free nature of integer mapping, the AI approach results in a much better reconstruction compared to conventional binary approach.

The blur noise present in the image is removed by the filter. In the encoding process of wavelet, the image is broken down into K*K blocks of pixels, where K denotes 2, 4, 6, etc... The wavelet coefficients are obtained from each block of input data. Then we encode the Feature points by applying discrete wavelet transform. At the receiver, the projections are retrieved (decoded) by IWAVELET and is used to reconstruct the image. The algebraic integer (AI) technique provides a simple representation for the irrational basis coefficients of the transform.
The DWT is given by,

$$D(u) = \alpha(u) \sum_{i=0}^{K-1} f(i) \cos\left[\frac{\pi(2i+1)u}{2K}\right] \qquad (3)$$

Here, u ranges from 0, 1 …K-1 and the wavelet coefficient is represented as *D (u)*. The inverse wavelet (IWAVELET) is expressed as,

$$f(i) = \sum_{u=0}^{K-1} \alpha(u) D(u) \cos\left[\frac{\pi(2i+1)u}{2K}\right] \qquad (4)$$

Apply inverse feature transform

Explicit and computationally efficient inversion formulas for the Feature transform and its dual are available. The process of feature transform is reversed here to obtain back the integer pixel values. The Feature transform in n dimensions can be inverted by the formula:

$$C_n f = (-\Delta)^{(n-1)/2} R * R_f \qquad (5)$$

$$\text{where}, C_n = (4\pi)^{(n-1)/2} \frac{\Gamma(\frac{n}{2})}{\Gamma(\frac{1}{2})} \qquad (6)$$

and the power of the Laplacian $(-\Delta)^{(n-1)/2}$ is defined as a pseudo differential operator.

Compute MSE and PSNR

The term MSE represents Mean Square Error. MSE is a performance measure for examining the quality of compressed image. In general, MSE is used along with PSNR analysis. It produces the distortion level by comparing the reconstructed image and the original image. The expression that helps the computation of MSE is given below:

$$MSE = \frac{1}{AB} \sum_{i=1}^{A} \sum_{j=1}^{B} (P_{i,j} - Q_{i,j})^2 \qquad (7)$$

The term P denotes the original image of size A x B whereas Q denotes the reconstructed image of size A x B.

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PSNR represents Peak Signal to Noise Ratio. PSNR value is the ratio between the signals to noise ratio of reconstructed image to the reference image and is calculated in decibels using the equation given below:

$$PSNR = 10\log_{10}\frac{I^2}{MSE} \tag{8}$$

After obtaining the reconstructed image, the computation of PSNR and MSE are carried out using the above two equations to measure the performance of the proposed image comparison ratio.

RESULTS AND DISCUSSIONS

An image of any size and resolution is taken and converted into a gray scale image, thus obtaining the binary points. From these points, feature extraction is done and then the AI based DAUB-6 wavelet transform and its inverse is performed. Again, from gray scale a compressed colour image is retrieved. Here, a default image is considered as an example.

First, the code for pre-processing step is run and a default chrysanthemum coloured image is selected as input, which is given in Figure-2. Then, it represents how the gray-scale image of fixed range [256, 256] is converted into a transformed image after the local binary point transform.

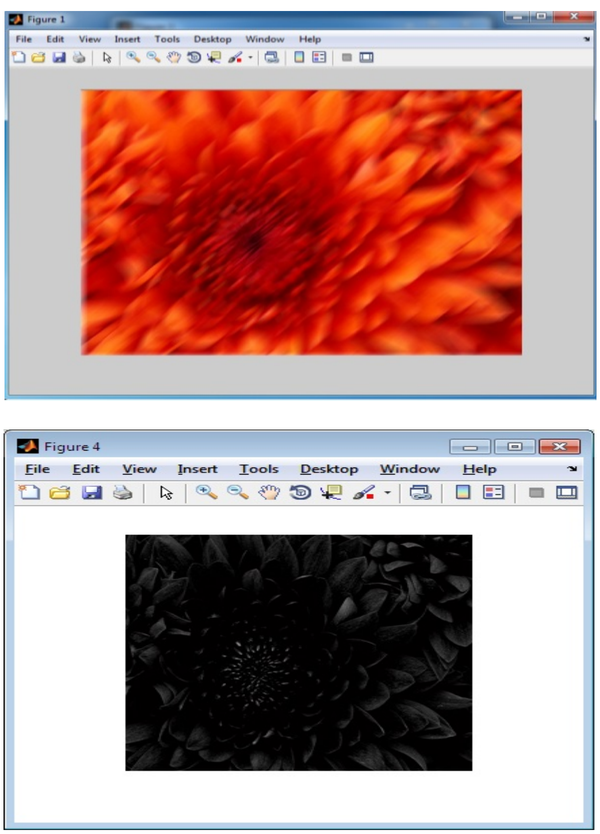

Figure-2. The default image and its feature transformed image.

The Figure-3 exhibits the activation process of simulation for the discrete wavelet filter bank and initializing the inputs for the buffer circuit of clock=1, enable=1 and reset=0 is done. It also shows the architecture of the filter bank.

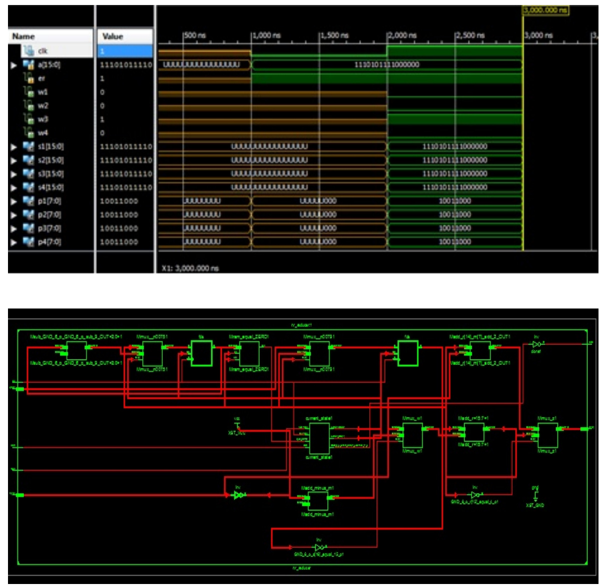

Figure-3. Initializing the buffer circuit for filter activation and the filter architecture's RTL view.

Figure-4 depicts the image that has passed through the wavelet filter bank architecture. It is again converted into binary image by the inverse feature transform. From these binary values the integer values are got while converting into a gray-scale image. Finally, the reconstructed coloured default compressed image is received. Then, the MSE, PSNR and Comparison Ratio are calculated and displayed.

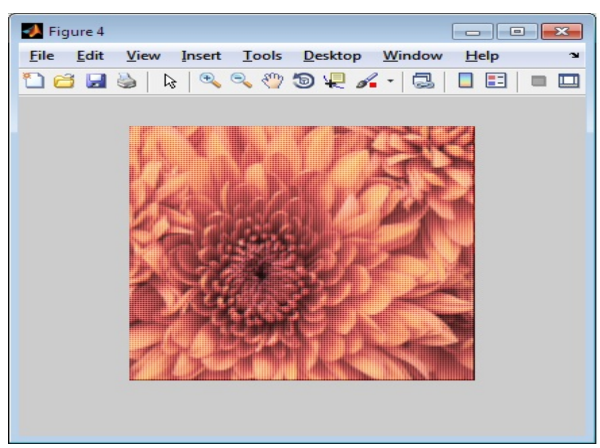

Figure-4. The reconstructed image.

Figure-5 depicts the chart for some test images their MSE, PSNR and Comparison Ratio. As per thresholding, the MSE values lie below 1.00 and PSNR values are high as expected. The comparison ratio is between MSE and PSNR. Table-1 depicts the calculated values for the adder count, speed, power and delay of the proposed architecture for a default image.

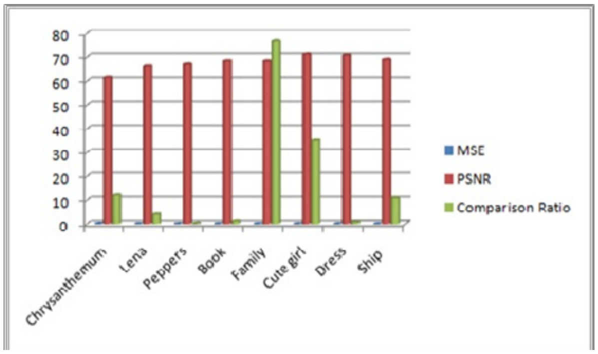

Figure-5. A chart on various test images and their image quality ratios.

Table-1. The calculated values of adder count, speed, power and delay of the proposed architecture.

Content	Values
PSNR	61.5738
ADDER	3570
DELAY(ns)	1.005
SPEED(MHz)	994.728
POWER(w)	0.009

CONCLUSION AND FUTURESCOPE

A 2D-Discrete Wavelet filter bank implemented using 6-tap Daubechies filter architecture is exploited as a tool for image compression technique. As proposed, it provides reduced adder count and path delay. It also removes blur noise, blocking artifacts and achieving preferred results for complex images, as they have best energy compaction capability for highly correlated images. The algebraic integer (AI) technique maps the irrational basis coefficients of the transform with the integers. This reconstructed compressed image by feature transform and wavelet filter bank provides good results. The compression performance (CP), objectively peak signal to noise ratio and subjectively visual quality of image are measured. As a future-scope, we try to implement this process in Xilinx Spartan®-6 LX45T FPGA or Virtex-6 LX240T FPGA family for medical applications.

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