# An Overview DWT Compression Technique Used For Cheque Truncation System of Bank.

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***Abstract*— A Cheque Truncation System (CTS-2012) has been applied by the banks throughout the country.CTS means that instead of sending the cheques in physical form by collecting the bank to the paying bank, an electronic image of cheque is transmitted to the drawee branch for payment through the clearing house, thereby eliminating cumbersome physical presentation of the cheque to the paying bank. Thus, saving time and cost involved in the traditional clearing system. The transmission of data i.e. cheques images requires more bandwidth for transmission. To transmit the cheques images using minimum bandwidth, it is going to discuss the use of the *"Discrete Wavelet Transforms Compression Techniques for cheques images transmission"*.**

***Keywords*— Transforms, DWT, Compression,Quantization.**

## I. INTRODUCTION

In general, image compression techniques can be broadly classified into:

- ❖ Lossless compression
- ❖ Lossy compression

In lossless compression, every bit of information is preserved during the decomposition process. The reconstructed image after compression is an exact replica of the original one. Such scheme only achieves a modest compression rate. It is used in applications where no loss of image data can be compromised. In lossy compression, a perfect reconstruction of the image is sacrificed by the elimination of some amount of redundancies in the image to achieve higher compression ratio. However, no visible loss of information is perceived under normal viewing conditions [2]. The type of image compression scheme that is focused on is the lossy compression scheme. A general lossy image encoder system consists of the three operations as shown in Figure 1.1.

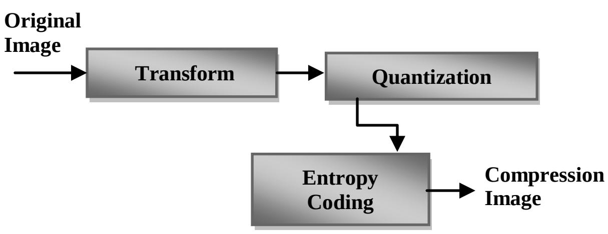



Fig: 1.1 Image Encoder Systems

The transform operation is a linear transform that aims to reduce the entropy of the image. This operation is reversible and does not cause any loss of information to the image. An example of such a transform operation is Fourier-based discrete cosine transform (DCT) or wavelet-based subband coding. The quantization operation, which is a lossy operation, maps a large set of input image data to a smaller set of output image data, attempting to remove redundancies in the image. This process is irreversible and it introduces distortion. Some examples of quantization are scalar quantization and vector quantization [1, 2]. The entropy coding operation, which is a lossless operation, compresses the image further without the loss of information. The main idea this paper is to reduce the average number of bits to represent an alphabet by assigning a longer codeword to an unlikely alphabet and a shorter code world to a likely symbol. Some common examples of entropy coding are Run-Length Encoding, Huffman Encoding and Arithmetic Encoding. To reconstruct the image, the operation get reversed as shown in Figure 1.2.at each stage, an inverse operation will be carried out.

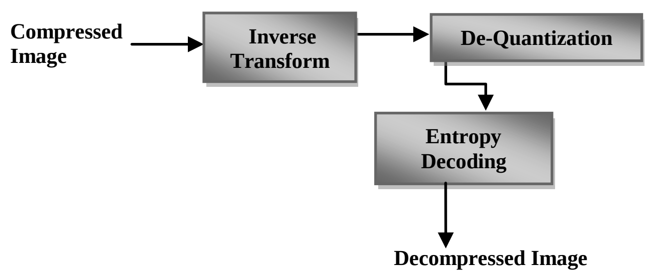



Fig: 1.2 Image De-coder Systems

With the help of these two system the CTS system of the bank will able to compressed an electronic image of cheque is transmitted from the drawee branch for payment to the clearing house through wired or wireless network channel by utilizing the minimum bandwidth of network.

## II. TYPE OF TRANSFORM USED FOR IMAGE COMPRESSION.

### *A. Fourier Transform.*

In the Fourier Transform, sinusoids are as the basis functions. Such functions have infinite energy across the domains and have been valuable in analyzing time invariant or stationary phenomena. It can be computed using the following equation:

$$F(\omega) = \int_{-\infty}^{\infty} e^{-j\omega t} f(t)\,dt \quad \ldots\ldots\ldots\ldots(i)$$

The FT gives the frequency information of the signal, which means that it tells us how much of each frequency exists in the signal, but it does not tell us when in time these frequency components exist. This information is not required when the signal is so-called stationary [2]. If there is a sudden change in time in the input signal, this transformation will result in the spreading of the frequency components throughout the entire duration of the signal. Thus, information about one instant of a signal cannot be obtained. Therefore this transformation is not suitable for non-stationary, time-varying phenomena whose frequency content changes with time [2].

*B. Short-Time Fourier Transform.*

To overcome the limitation of the FT, a window-version of Fourier Transform known as Short Time Fourier Transform (STFT) was developed. In STFT, we can divide the non-stationary signal into small segments where each segment of the signal is assumed to be stationary. Then we apply STFT on these segments using the following formula:

$$STFT(t,\omega) = \int_{\infty}^{\infty} e^{-j\omega t} f(s)\, g(s-t)\; ds \ldots..(ii)$$

But again there is a resolution problem here. Once the size of the STFT.s window is chosen, the time-frequency resolution is fixed for the entire time-frequency plane as illustrated in Figure 2.1. Moreover, the resolution in time ($\Delta t$) and frequency ($\Delta f$) cannot be made arbitrarily small at the same time because their product is lower bounded by the Heisenberg inequality.

$$\Delta t \Delta f \geq \frac{1}{4\Pi} \quad \ldots\ldots\ldots\ldots(iii)$$

This inequality means that the trade off time resolution for frequency resolution and vice-versa. That is, for a good frequency resolution, poor time resolution has to be accepted. Likewise, for a good time resolution, it has to be settled for poor frequency resolution [2].

*C. Wavelet Transform.*

The wavelet transform allows resolving the resolution problem that gets encountered in STFT. The basic functions allow to trade off the time and frequency resolution in different ways. To analyze a large region of low frequency signal, a wide basis function is used. Similarly, to analyze a small region of high frequency signal, a small basis function is to be used. The basic functions of the wavelet transform are known as wavelets. There are a variety of different wavelet functions to suit the needs of different applications. In general, a wavelet is a small wave that has finite energy concentrated in time. It is this characteristic about a wavelet that gives it the ability to analyze any time-varying signals [2, 5, and 9].

There are two types of wavelet transform which are discussed in this Paper. They are the continuous wavelet transform (CWT) and discrete wavelet transform. (DWT). The main idea about the wavelet transform is the same in both of these transforms. However, they differ in the way the transformation is being carried out [1, 3, and 11].

In CWT, an analyzing window is shifted along the time domain to pick up the information about the signal. This process is difficult to implement and the information that has been picked up may overlap and result in redundancy. In Still Image Compression using Wavelet Transform 8 DWT, signals are analyzed in discrete steps through a series of filters. This method is realizable in a computer and has the advantage of extracting non-overlapping information about the signal [4, 5].

*D. Continuous Wavelet Transform.*

In continuous wavelet transform (CWT), information about a signal is obtained by manipulating the wavelet functions along the time axis as shown in the following equation.

$$y(S, T) = \int f(t)\, \varphi(t)\; dt \quad \ldots\ldots\ldots\ldots\ldots\ldots(iv)$$

Where $\varphi(t) = 1/\sqrt{S}\; \varphi\left(\frac{t - T}{S}\right)$

The function, φ (t), is called the mother wavelet. This function serves as a prototype for generating other window functions. The term translation,φ, refers to the location of the window. As the window shifts through the signal, the time information in the transform domain is obtained. The term scaling, S, refers to dilating or compressing the wavelet. The relationship between the time and frequency is shown in Figure 2.1. Each window corresponds to a value of the wavelet transform in the time-frequency plane. Note that the area of the windows is constant but the widths and heights vary. The parameter scale used in wavelet transformation is similar to the scale used in the maps. At high scale, the wavelet seeks for global information or low frequencies information about the signal. At low scale, the wavelet seeks for detailed information or high frequencies information about the signal [3, 4, and 7].

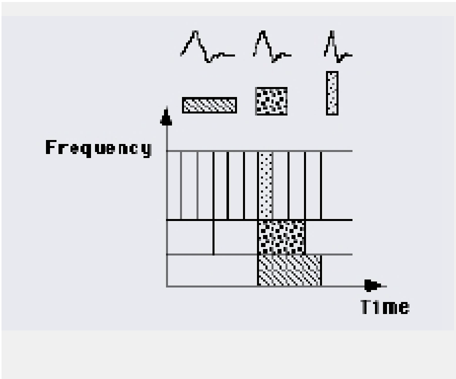


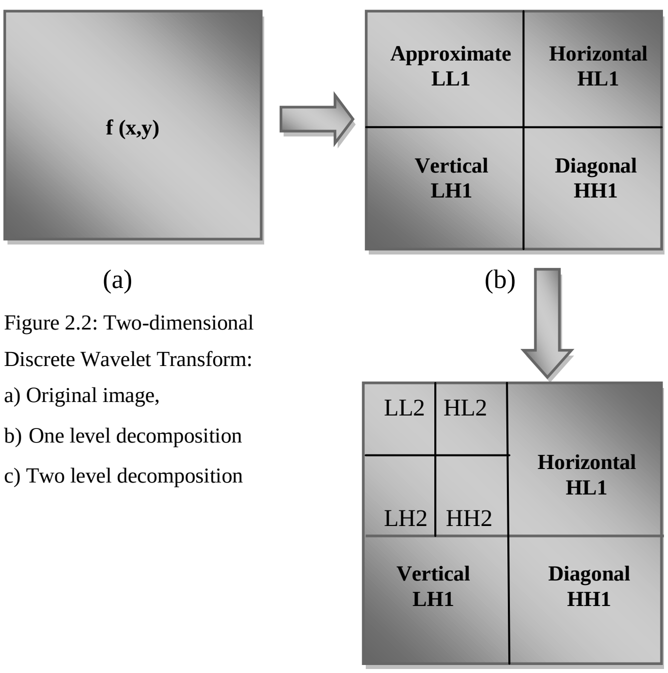

Figure 2.1: The relationship between the time and frequency

At high frequencies, this window will have a narrower width that corresponds to good time resolution and a longer height that corresponds to poor frequency resolution.

At low frequencies, this window will have a wider width that corresponds to poor time resolution and a shorter height that corresponds to good frequency resolution. Such analysis approach is suitable for most signals since most of the high frequencies occur for a small duration of time while low frequencies occur for long duration of time [1, 2].

*E. Discrete Wavelet Transform.*

In the discrete wavelet transform, an image signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation. This analysis filter bank, which consists of a low pass and a high pass filter at each decomposition stage, is commonly used in image compression [1, 2]. When a signal passes through these filters, it is split into two bands. The low pass filter, which corresponds to an averaging operation, extracts the coarse information of the signal. The high pass filter, which corresponds to a differencing operation, extracts the detail information of the signal. The output of the filtering operations is then decimated by two. A two-dimensional transform can be accomplished by performing two separate one-dimensional transforms. First, the image is filtered along the x dimension and decimated by two. Then, it is followed by filtering the sub-image along the y-dimension and decimated by two. Finally, the image is splitted into four bands denoted by LL, HL, LH and HH after one-level decomposition. Further decompositions can be achieved by acting upon the LL subband successively and the resultant image is split into multiple bands as shown in Figure2.2.




(a) (b) (c)

Figure 2.2: Two-dimensional Discrete Wavelet Transform:
a) Original image,
b) One level decomposition
c) Two level decomposition

In mathematical terms, the averaging operation or low pass filtering is the inner product between the signal and the scaling function *(Φ)* as shown in Equation , whereas the differencing operation or high pass filtering is the inner product between the signal and the wavelet function *(ψ)* as shown in Equation.

Average coefficients,

$$Cj\ (k) = <f\ (t), \phi,u\ (t)> = \int f(t)\ \phi,u\ (t)\ dt$$

Detailed coefficients,

$$dj\ (k) = <f\ (t), \varphi_{jk},(t)> = \int f(t)\ \varphi_{jk},(t)\ dt$$

The scaling function or the low pass filter is defined as

$$\phi,u\ (t) > = 2^{\int/2}\ \phi,(2^{t}\ t - k)$$

The wavelet function or the high pass filter is defined as

$$\varphi_{jk}\ (t) = 2^{\int/2}\ \varphi\ (2^{\int}\ t - k)$$

Where *j* denotes the discrete scaling index and *k* denotes the discrete translation index. The reconstruction of the image can be carried out by the following procedure. First, up sample it by a factor of two on all the four subbands at the coarsest scale, and filter the subbands in each dimension. Then sum the four filtered subbands to reach the low-low subband at the next finer scale. Repeat this process until the image is fully reconstructed [1, 3, 4, 8, and 9].

In this paper, it is going to discussed working of *"A DWT Compression Technique used for the Cheque Truncation System of Bank."*

## III. VARIOUS TYPES OF QUANTIZATION AND ENTROPY ENCODING.

Quantization, is a process of mapping a set of continuously valued input data, *x*, to a set of discrete valued output data, *y*.

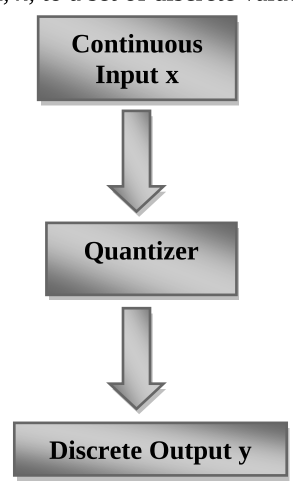



Figure 3.1: Quantizer

The following are some of the scalar quantizers:

- Uniform quantizer
- Subband uniform quantizer
- Uniform Dead-Zone Ouantization

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waste of storage space if we were to save the redundancies of the quantized data. One way of overcoming this problem is to use entropy encoding. It is an example of a lossless data compression technique that provides a means of removing the redundancies in the quantized data without any loss of information [2].

The two types of lossless data compression schemes are:-

- Huffman Encoding
- Run-Length Encoding.

## IV. IMAGE COMPRESSION USING WAVELET TRANSFORMS.

In this section, the compression techniques and steps used to compress a two-dimensional 256-by-256 gray-scale digital image are discussed.

The steps that are used to compress this 2-D image are described as follows:

1) Read the image from the source
2) Perform operation for the image decomposition
3) Use 'wdencmp'for compression processes of a signal or a image using wavelet.
4) By varying the wavelets (W), decomposition level (n) and the Threshold value (thr), can change the compression level.
5) Calculate the percentage of compression

### *A. Wavelet Transform.*

The one-level decomposition process begins with the convolution of the low-pass filter with all the rows of the image, followed by a down sampling of two. Then, it continues with the convolution of the high pass filter with all the rows of the image, followed by a down sampling of two. This process is then repeated for all the columns of the image.

If further decomposition operations are desired, they can be carried out by acting upon the LL sub-image successively.

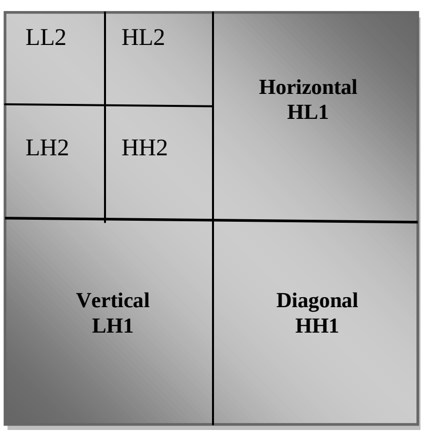


Figure 4.1 shows the output of two-level decomposition

The following flowchart illustrates the implementation of the two-dimensional Discrete Wavelet Transform:

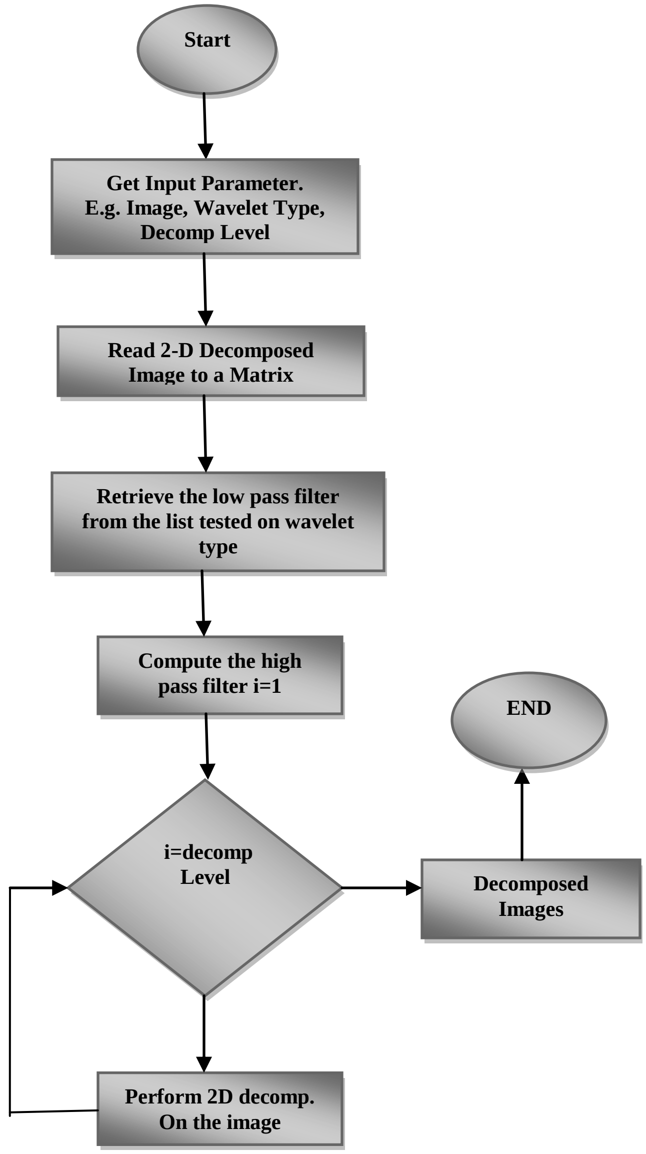


Figure 4.2: Flowchart for general decomposition of two dimensional forward DWT.

One point to note is that the size of the decomposed image still remains as a 256- by-256 image. However, the data type of the wavelet coefficients has changed from integer to floating data type. Therefore the overall size of the decomposed image has increased dramatically [3, 5, 6, and 7].

To reconstruct the image, an inverse DWT is applied. The low pass coefficients are defined as:

$$\beta 1=\frac{1-\sqrt{3}}{4\sqrt{2}} \quad \beta 2=\frac{3-\sqrt{3}}{4\sqrt{2}} \quad \beta 3=\frac{3+\sqrt{3}}{4\sqrt{2}} \quad \beta 4=\frac{1+\sqrt{3}}{4\sqrt{2}}$$

And the high pass coefficients are defined as:

$$\alpha 1=\frac{-1+\sqrt{3}}{4\sqrt{2}} \quad \alpha 2=\frac{3+\sqrt{3}}{4\sqrt{2}} \quad \alpha 3=\frac{3-\sqrt{3}}{4\sqrt{2}} \quad \alpha 4=\frac{1-\sqrt{3}}{4\sqrt{2}}$$

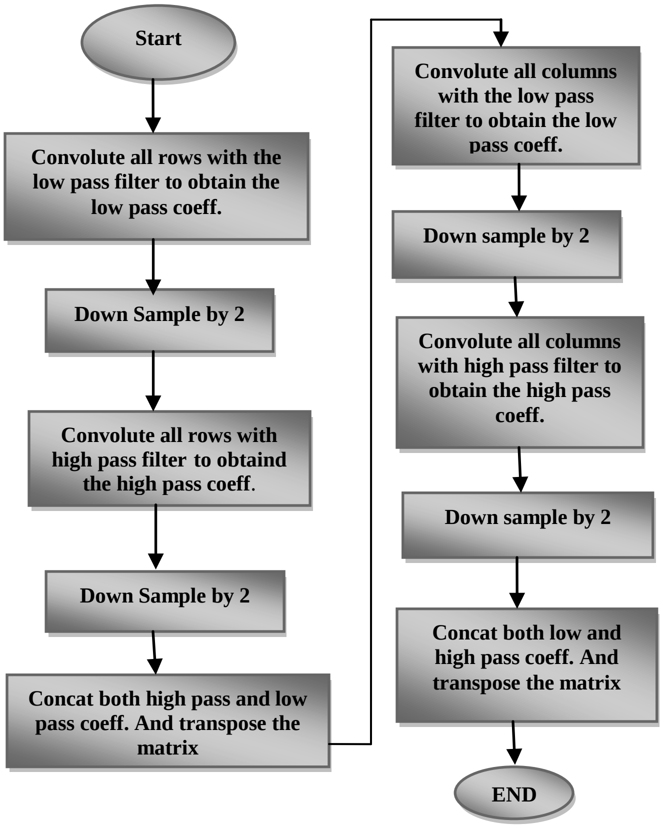


Figure 4.3: Flowchart for detailed decomposition breakdown of two dimensional forward DWT.

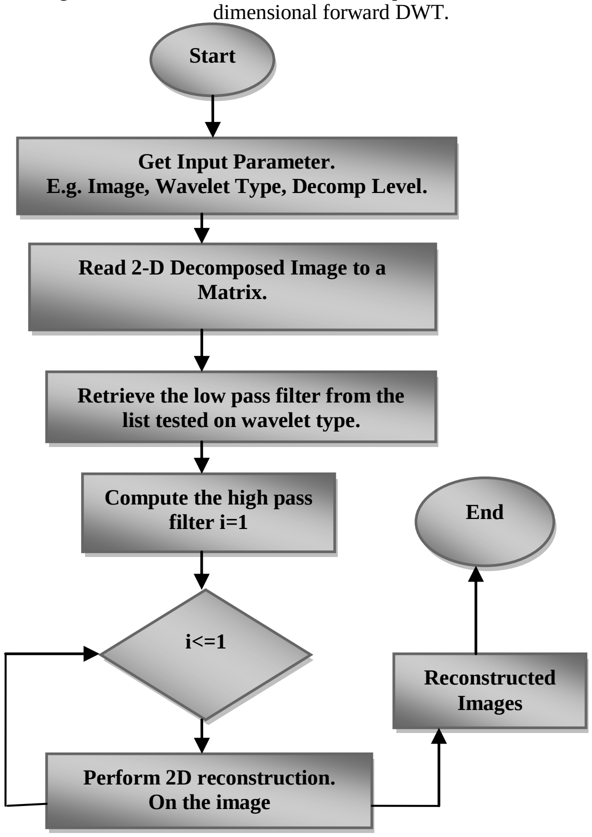


Figure 4.4: Flowchart for general reconstruction of two dimensional inverse DWT.

The above flowchart illustrates the implementation of the two-dimensional Inverse Discrete Wavelet Transform.The reconstruction of the image starts from the most inner band. Assume a two level decomposition is carried out and the output is shown in Figure 4.4. To reconstruct this image, action is to be taken upon the sub-images of the second level. These include the LL2, HL2, LH2 and HH2 sub-images. These sub-images are passed to the inverse DWT operation to obtain the LL1 sub-image. Then this process is repeated until the recovery of the original image.

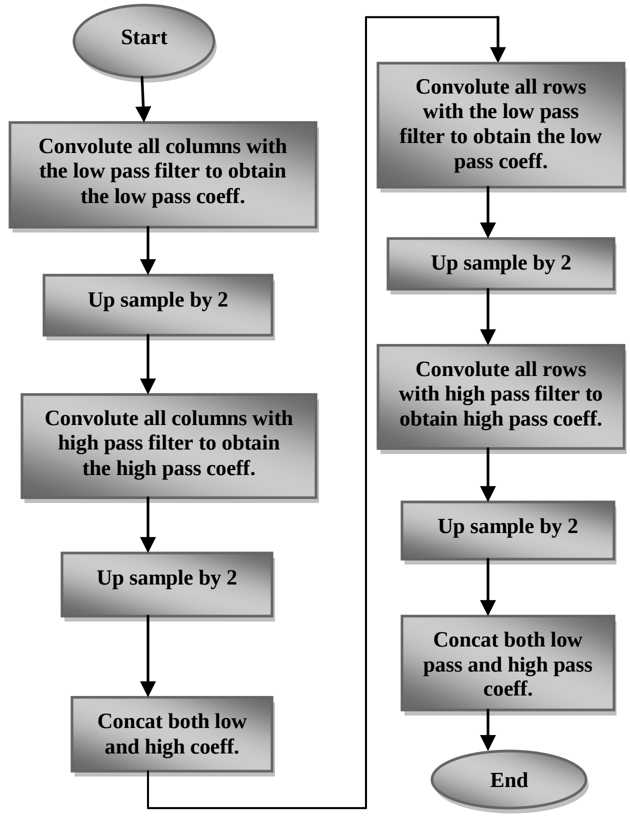


Figure 4.5: Flowchart for detail reconstruction breakdown of two dimensional inverses DWT

### *B. Algorithm for Image Compression.*

In this section, the compression techniques and algorithms used to compress a two-dimensional 256-by-256 gray-scale digital image are discussed. These algorithms are implemented using Matlab 6.5.

The steps that are used to compress this 2-D image are described as follows:

- Read the image from the source.
- Save the image in the matrix form .
- Make subplot of original image titled as 'Original Image'.
- Use 'wdencmp'for compression process of a signal or a image using wavelet.

- By varying the wavelets (W), decomposition level (n) and the Threshold value (thr), can change the compression level.
- Calculate the percentage of compression by using following Equation:-

  Perfo=100X (length (find (cxd==0))/length (cxd))
- Assign y=wcodemat for extended pseudo color matrix scaling.
- Save the image in the matrix form.
- Reconstruct the original image from X1 & X2, where, X1 taken as approximation coefficient and X2 taken as detailed coefficient.
- Make subplot of compressed image titled as 'compressed image'

## V. RESULTS

The quality of image in the lossy compression technique is very important. During experimentation it is found that the factors such as decomposition (n) and image threshold (thr) affect the quality of reconstructed image. In this paper, stress is given on identification of the optimum values of n and threshold to get comparatively good quality reconstructed output. Accordingly Matlab program is developed to perform the wavelet compression, decompression for various values of n and threshold. The program also generates the analysis data and the same is plotted using Matlab for various values of n and threshold. In this regard the tool for measurement of the quality of image is human eye. The different compressed images & the related graph showing the relation between threshold levels and percentage compression at different decomposition levels.

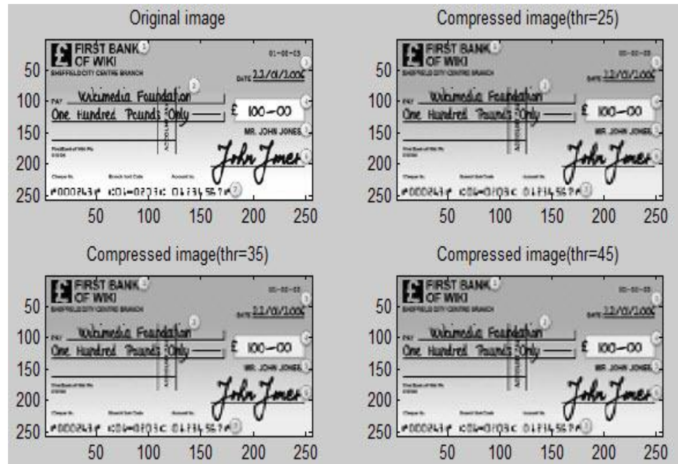


Figure5.1: Original image and compressed image of bank cheque at different threshold for first level decomposition.

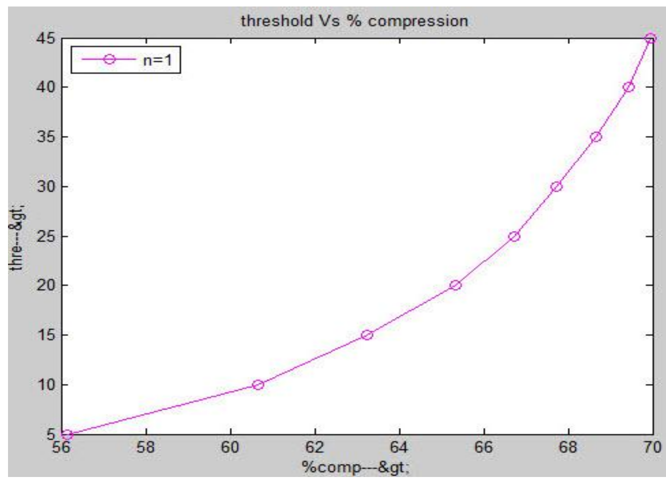


Figure5.2: Graphical representation threshold v/s Compression percentage of bank cheque for first level decomposition.

*A. Observation Table for n=1.*

| Sr.No | Threshold | Compression in Percentage |
|---|---|---|
| 1. | 5 | 56.1475 |
| 2. | 10 | 60.6544 |
| 3. | 15 | 63. 2489 |
| 4. | 20 | 65.3341 |
| 5. | 25 | 66.7132 |
| 6. | 30 | 67.7408 |
| 7. | 35 | 68.6662 |
| 8. | 40 | 69.4279 |
| 9. | 45 | 69.9552 |

*B. Observation Table for n=2.*

| Sr.No | Threshold | Compression in Percentage |
|---|---|---|
| 1. | 5 | 66.6206 |
| 2. | 10 | 72.2007 |
| 3. | 15 | 75.5847 |
| 4. | 20 | 78.2485 |
| 5. | 25 | 80.1045 |
| 6. | 30 | 81.5523 |
| 7. | 35 | 82.8292 |
| 8. | 40 | 83.9651 |
| 9. | 45 | 84.8293 |

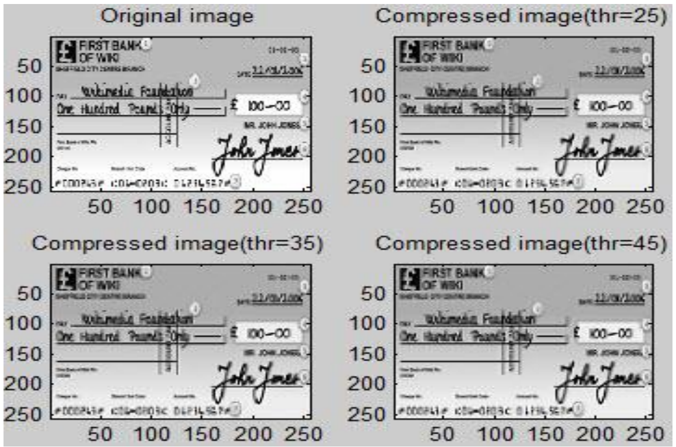


Figure5.3: Original image and compressed image of bank cheque at different threshold for second level decomposition.

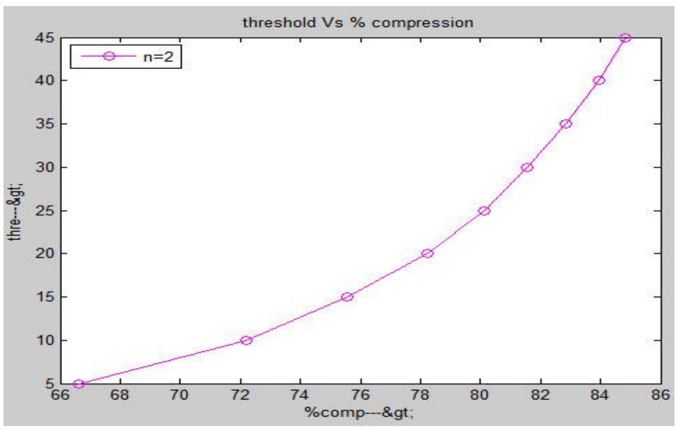


Figure5.4: Graphical representation threshold v/s Compression percentage of bank cheque for second level decomposition.

## VI. CONCLUSION

Image coding standards to date have used DCT-based encoding. However, it is likely that other less mature coding techniques will eventually prove capable of outperforming DCT-based compensation methods. For example, the most promising techniques could be based on wavelet transform as well as which exploits the knowledge of underlying images to be compressed. In this paper, we have proved that the quality of a lossy compressed cheque image depend on a number of factors. From the discussion. it has been gathered that the threshold level, decomposition level are some of the more important factors. These new approaches take into account the human visual systems (HVS) for selecting the technique for the applications. Higher Compression Ratios can be achieved at the expense of the quality of the image by increasing the threshold & decomposition levels which requires minimum bandwidth for transmission of compressed cheque of banks to the drawee branch for payment through the clearing house.

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