Digital Image Watermarking Using Fast Fourier Transform To Minimization of Different Attacks

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Abstract— The real world of today is that of the digital world. Digital data is being used immensely in every field nowadays. Copying computer data without lack of accuracy isn't so difficult. And the risks of copying these digital data are higher. So, there's a big need to ban digital media from such illegal copyright. Digital watermarking (DWM) is a solid solution to this problem. Digital watermarking is nothing more than the technology in which several data are embedded into digital content that we have to secure from illegal copying. Digital watermarking has various applications such as fingerprinting, owner identification and so on. Digital watermarks are durable, porous, transparent, and invisible, of different types. Digital watermarks have some demands as integrity, robustness and complexity. This project presents a digital watermarking image based on two-dimensional discrete wavelet transformation (DWT2), two-dimensional fast Fourier transformation (FFT2), two-dimensional discrete cosine transformation (DCT2) and. Signal to noise ratio (SNR) and similarity ratio (SR) are determined for each transform to determine the image quality.

Keywords: Invisible watermarking, Discrete Wavelet Transform (DWT), Fast Fourier Transform (FFT)

I. WAVELET TRANSFORM THEORY

1) *Wavelet Compression-*

This section presents a Summarize compression description using wavelets.

2) *Wavelets-*

A wavelet's fundamental definition is simply a function with a well-defined temporal support that wiggles over the x-axis (it has the same area above and below the axis). However, this concept does not benefit us much, so to clarify what the wavelet analysis so wavelet transforms is a better approach.

The underlying Wavelet Transformation is close to the well-known Fourier Transform. Like the Fourier Transform, the coefficients are determined by an input signal component with a collection of orthonormal simple functions spanning (although this is a small subset of all wavelet transforms available). The difference is in how these functions are designed, and more specifically in the types of analysis that they allow [1].

The key difference is that the Wavelet Transforms is a multi-resolution transformation, that is, it allows for a form of time-frequency analysis (or wavelet-speaking translation-scale). The effect is a very precise interpretation of the frequencies found in the signal by using the Fourier Transforms with little details about when those frequencies happened. We get information in the wavelet transform on when those features happened, and about the signal's scale characteristics. Scale is frequency equivalent and is a function of the amount of information in the signal. Small scale is related to the number of coefficients and therefore counterintuitive to detail level [2].

The discrete Wavelet Transform may be described as a series of (time-decimating) filtering and sub-sampling. In each step of this sequence a range of 2j-1 coefficients is determined, where the scale is j < J and the number of samples in the input signal is N = 2J. Calculating the coefficients by applying a high-pass wavelet filter to; signaling and down-sampling the output by a factor of 2. Around the same level, it also conducts a low-pass scale filtering (followed by down-sampling) to generate the signal for the next level. Both the wavelet and the scale filters can be obtained from a single wavelet-defining Quadrature Mirror Filter (QMF) function.

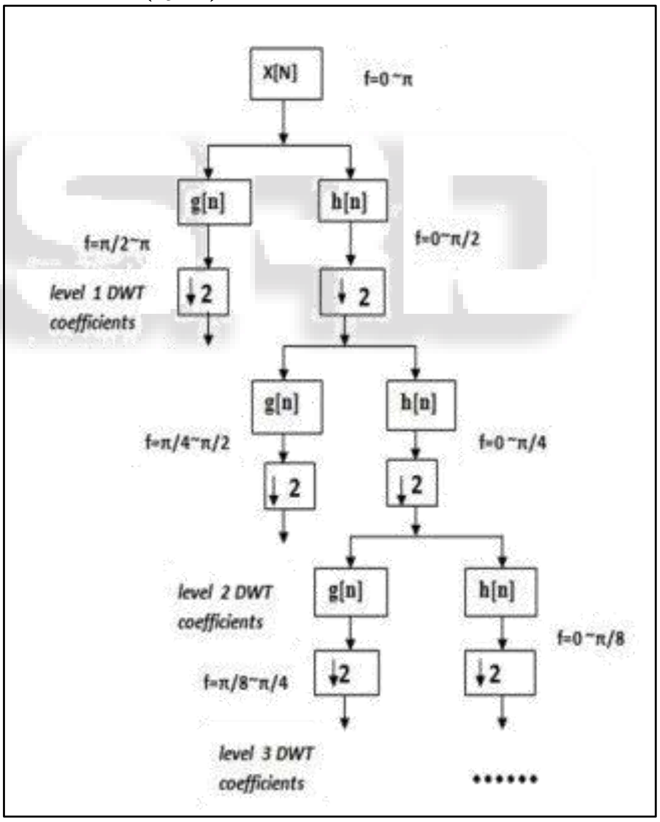

Fig. 1: level of scale DWT coefficient

The range of scale -coefficient corresponds to a signal "smoothing" and information elimination, while the wavelet-coefficients refer to the "differences" between the sizes. Wavelet theory shows that from the coarsest coefficients of scale and the series of coefficients of wavelet [2]. Reconstruction of the original signal. The cumulative number (scale + wavelet) of coefficients is proportional to the number of samples in the signal.

B. The Compression Wavelet

Why can we use the coefficients of these transformations to achieve compression? With very few large coefficients, the distribution of values for the wavelet coefficients is usually centered around 0. It means that virtually all information is contained in a small fraction of the coefficients, which can be compressed easily. This is done by quantizing the histogram based values and encoding the result in an efficient manner. Z.B. Encoding to Huffman. We will use a simpler method for that homework. And instead of quantizing we are going to eliminate all coefficients except the largest M. This provides a compression ratio of about 2M / N (the factor of 2 is for storing both the value and the index coefficient).

C. Why Wavelets Are Useful?

Wavelets have a number of interesting applications, some of which are given below. How-ever, wavelet applications are limited in themselves. More significant are the theories behind wavelets, which we will discuss in this lecture and in subsequent lectures.

The most common use of wavelets is for applications in signal processing. For instance. Anwendungen for compression. When we can establish an adequate signal representation, we can remove the "less important" bits of the representation and thereby retain the original signal relatively intact. This involves a transition that distinguishes the "essential" pieces of the signal from those of lesser significance.

In the simplest case, we can decompose a signal into two parts: a part of low frequency, which is some sort of average of the original signal, and a part of high frequency, which is what remains after the part of low frequency is subtracted from the original signal. We are interested in the low frequency portion and thus disregard the high frequency portion, what remains is a clearer image of the original signal with its preserved components of low frequency. Instead, if we're more involved in the high frequency part, then we would be able to remove the low frequency portion [2].

This technique that of breaking down a signal into two sections, is popular in all wavelets. A hierarchical decomposition is also central to the wavelet analysis, in which we will apply further transformations to an already decomposed signal.

- Identification at the bottom. For this method the region in which the input picture changes rapidly is most important to identify [2]. We should discard the sections which are smooth (low frequency). For this application is suitable the simplest wavelet basis, the HAAR basis (to be discussed later).
- Along that vein, Strang and Nguyen's book describes a widely used wavelet application, fingerprint compression, in which edge detection figures prominently.
- Images. Two notable computational applications of wavelets are
  1) Curve representations and surface representations; and
  2) Radiosity to wavelet.

  Those two reflect two very different wavelet uses.
- Review of amounts. To solve partial differential equations and integral equations, wavelets are used.

1) History of Wavelets

Wavelets were first used by HAAR in 1909. He was interested in finding a basis in frequency space on a functional space similar to that founded by Fourier. For mechanics, wavelets have been used in the Brownian motion characterization. This work led to some of the ideas which were used to build wavelet bases. Wavelets have also been used to analyze the coherent state of a specific quantum system. Finally, S., in the field of signal processing Mallet found that filter banks have significant connections to wavelet base functions [2].

D. Filters and Filter Banks

1) Linearity and Time Invariance

Consider x (n), filter H, and output y (n), a discrete input signal. On the input signal x we express H's operation as y = Hx.

If the input scales the output, we call the filter H "linear," and we call H "Time Invariant" if the output shifts correspondingly by shifting the input (in time). In these notes it is assumed that all filters are linear and time invariant [2].

2) Filter Operation

If H is linear and time invariant, its action can be expressed as follows:

$$y(n) = \sum_k h(k)x(n-K).$$

That operation is known as convolution. The individual coefficients h (I) are the system's "impulse responses".

The equation y = Hx can also be written as an infinite matrix, with vectors of the y and x columns and H as follows:

$$X = \begin{bmatrix} .... & ..... & ..... & ...... & ...... & ..... \\ .... & h(1) & h(0) & h(-1) & ...... & ...... \\ .... & ..... & h(1) & h(0) & h(-1) & ...... \\ ..... & ..... & ...... & ...... & ...... & ...... \end{bmatrix}$$

We know that the entries of the filter are in reverse indexed order. If the input stream s finite with n elements, H is a finite n x n matrix.

3) Filters And Wavelets, Haar Filters

Every base of a wavelet has two related filters. Those filters are generally expressed in the form

$$Y(n) = \sum h(n)x(n).$$

The basis for hair is especially simple. Both filters are H0 and H1 and have the following definitions:

$$H_0\ y(n) = \frac{1}{2}x(n) + \frac{1}{2}x(n-1)$$

$$H_1\!:\ y(n) = \frac{1}{2}x(n) - \frac{1}{2}x(n-1)$$

For H_0, all h coefficients are zero except for $h_0(0) = ½$ and $h_0(1) = ½$.

Similarly, in

H_1, $h_1(0) = ½$ and $h_1(1) = -½$.

H0 calculates its input by a moving average, resulting in a sequence that is smoother than the initial sequence. Therefore it's a low pass filter. H1 calculates the difference in motion and serves as a filter for high passes.

E. Scaling Functions and the Dilation Equation

We define a function ϕ as a "scaling function" Scaling functions obey the dilation equation,

$$\phi(t) = 2\sum h_0(k)\phi(2t-k). \qquad (1)$$

Note that the filter coefficients that are used (the h0's) are from the first filter pair. Afterwards we will use the second filter.

If this equation has an appropriate solution ϕ (t), then we can construct a frame using any integral values of j or k in the following generating relation.

$$\phi(2^j t-k) \qquad (2)$$

Next we introduce the wavelet equation (3), which uses the coefficients from the second pair of filters:

$$w(t) = 2\sum h_1(k)\phi(2t-k). \qquad (3)$$

We generate a wavelet basis with a similar generating relation

$$w(2^j t - K).$$

Remember that scaling functions are not a basis for this; wavelets are. Yet wavelets are constructed from scaling functions so first we need to find a scaling function.

As can be seen from the wavelet equation, wavelets are defined as linear combinations of scaling functions one step below where the set of all scaling functions generated with a given J is known as a "point."

For instance, the Haar scaling function satisfies the dilation equation with the solution

$$\phi(t) = \phi(2t) + \phi(2t-1).$$

And the Haar wavelet satisfies the wavelet equation with the solution

$$w(t) = \phi(2t) + \phi(2t-1).$$

The base of the hair covers the space with integrable square of all the functions. Wavelets on hair are orthogonal.

F. Filters and Filter Banks

1) Definition of Several Operators

Here we will define four operators and describe their operation (Figure1).

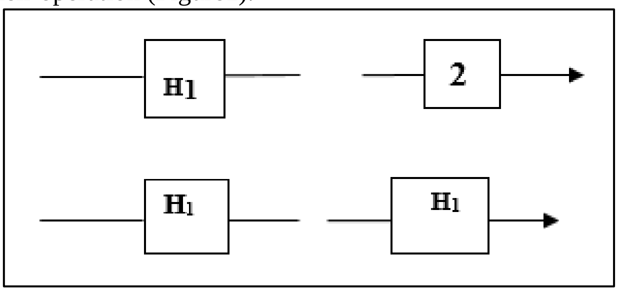

Fig. 2: Our 4 Operators

The first operator, H= H_0, is the Haar moving average filter. It outputs its current input average and previous input averages.

The second operator, H1, is the Haar moving difference filter. It produces half the difference between the present input and prior input.

The third operator, 2 is an operator with up sampling. Each input twice, its input rate is doubled.

A down-sampling operator is the fourth operator, 2,. It outputs every other input that it receives, outputting at half the input rate.

2) Overview

We're going to look at two filter banks, one analytics bank and a synthesis bank. The Haar filter pair, consisting of a low pass and a high pass filter, will be used by the analysis bank. We would like to select a synthesis filter bank such that the output of the series-connected analysis and synthesis filter is the same as the input into the analytics filter, probably with a delay in time.

We must first look at the analytics bank, then the synthesis bank, then bring them together to prove that the above property retains them.

3) Haar Analysis Bank

The data comes in from the left side, and the filter bank's output exits on the right side along the two directions. It is ideal (but not required) that the system's bandwidth and storage specifications be equal to those of the input source.

The down sampling operators therefore cut the bandwidth of each of the two output streams in half (compared to that of the input stream) and the overall bandwidth requirement entering the analysis bank is equal to that leaving the bank

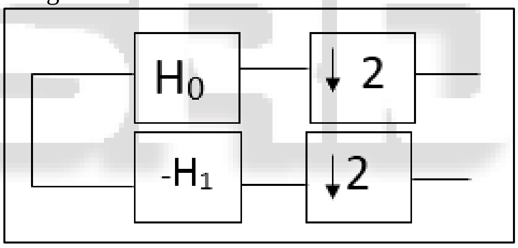

Figure 3: The basic Haar bank

In this case the filter bank can be interpreted as linear transform: if the input signal has finite length n, the output would always have length n, consisting of two parts, each with length n/2.

4) Synthesis Bank

With the aforementioned analytical bank, what synthesis bank can we use to reproduce the output input? Figure 3 shows the shape of the basic filter analysis. The output of both of the up sampling filters has the same bandwidth as the initial input stream but note the outputs of the F and G filters are combined to create an output stream of the same bandwidth as the original input.

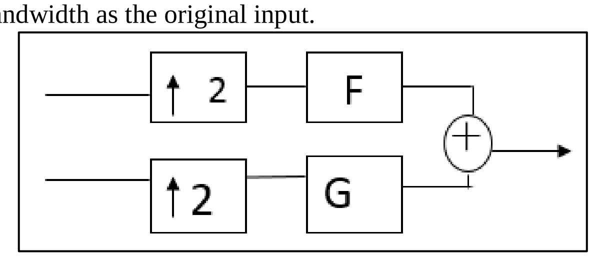

Fig. 4: The basic synthesis bank

Conveniently enough, it turns out that we can overwrite G with -H1 as the F filter in Figure 3 and likewise with the hair moving average filter H0. Figure 4 shows the structure of..

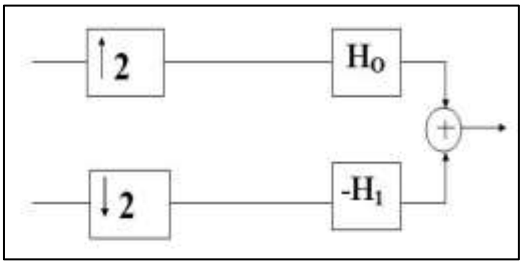

Fig. 5: The Haar synthesis bank

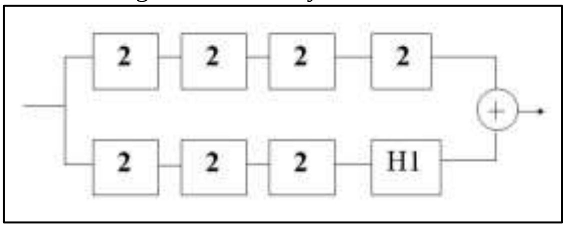

Fig. 6: The complete system

G. Transforms Used For Analysis and Construction of Filters

Two related transformations are the Fourier transform, and the z transform. Please consult the class-distributed handout "Ant aliased shifting and resizing" to see more background on Fourier transforms. All transformations are described in depth for most books on the signal processing.

1) THE FOURIER TRANSFORM

The Fourier transform is defied on both a discrete signal x(k) as

$$X(w)= \sum_k x(k)e-^{jkw} \quad (4)$$

and a continuous signal x(t) as

$$X(w) = \sum_k x(k)e-^{jkw} \quad (4)$$

Following the signal processing tradition, we use j to denote $\sqrt{-1}$.

2) Frequency Response

The frequency response of a filter H is written as H(ω) or H(e^{jw}).In Fourier space, the frequency response is useful for evaluating liner time invariant filters. Why? Convolution (i.e. the operation we use to define filter operation) is essentially multiplication. In other words, the operation

$$y(n) = \sum_k h(k)x(n-k)$$

in Fourier space is equivalent to

$$Y(\omega) = H(\omega)X(\omega)$$

So we can see that H, which is used as a filter, serves to highlight or de-emphasize input signal frequencies. Increasing frequency part of the frequency input is scaled by. For example, a low-pass filter passes through small-scale components (H(a) is close to 1 when /a is small) and suppresses high-frequency components (H(a) is close to 0 when /a is close to /)

We can see, then, that $H(\omega)$, used as a filter, serves to emphasize or deemphasize frequencies in the input signal. Each frequency component of the input $X(\omega)$ corresponding to a frequency ω is scaled by $H(\omega)$. For example, a low-pass filter passes through components with small ω (H(ω) is close to 1 when ω is small) and suppresses high-frequency components (H(ω) is close to 0 if ω is close to π)

3) Frequency Response Of The Haar Basis

First, we will look at the frequency response of H_o, the moving average function. Recall that the frequency response of an input stream is defined (4). In H_o the only coefficients that are non-zero are h (0) =h (1) =1/2. Thus, we can calculate the input response using (4):

$$H_0(\omega) = (1 + e^{-jkw})/2$$

$$= e^{-jkw/}/2(e^{jkw/2} + e^{-jkw/2})/2$$

$$= e^{-jkw/2}(e^{jkw/2+} + e^{-jkw/2})/2$$

$$= e^{-jkw/2}\cos(\omega/2)$$

And /H_o (ω)/=cow (ω/2).

With a similar derivation we can show that

$$|H_1(\omega)| = |\sin(\omega/2)|$$

a) SIMULATION RESULT-Figure 7(a) shows Lena and Figure 7(b) 512x512 watermark copyright gray scale cover image.


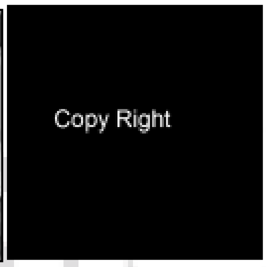

Fig. 7: a) Cover Image Figure 7: b) Watermark Image

Five types of attacks applied to the watermarked image after running code and achieve desired result. In Figure 8, the targeted images are displayed along with the methods and parameters used for the attacks. The number below each picture beside the mark denotes the SNR value. Figure 9 contains watermarks for each of the attacks, extracted from the watermark. Next to the photos the numbers are SF values. According to Figure 8 and Figure 9, the resistance of watermarked picture for each attack can be noted using either subjective human judgment or unbiased SF.

		
JPEG 75: 88.5529	Salt& peppers noise (0.02): 31.4704	Without attacks: 42.1500
		
Bluring: 30.4842	Rotating :35° 0.8799	Gaussian noise (0.025): 11.159

Fig. 8: Extracted watermark after different types of attacks

		
JPEG 75: 0.9992	Salt& peppers noise (0.02): 0.5542	Without attacks: 1
		
Bluring: 0.6192	Rotating :35° 0.0923	Gaussian noise (0.025): 0.2879

Fig. 9: Extracted watermark after different types of attacks

In the Figure above we have extracted watermarks after different type of attacks applying on the watermarking image, we can note that this method robust against JPEG compression.

II. Comparison between DCT and FFT

We can note that the DCT and FFT algorithms are the same, as discussed in two previous chapters. The process doesn't change; we can easily change the type of transformer by summing up the insertion and retrieval of watermark process. The outcomes will show the different between the two types,

Type of attack	FFT scheme
JPEG 75	88.5529
Salt & peppers noise	31.4704
Gaussian noise	11.159
Rotating 35°	0.8799
Blurring	30.4848

Table 1: Different types of attack FFT

Type of attack	FFT scheme
JPEG 75	0.9992
Salt & peppers noise	0.5542
Gaussian noise	0.2879
Rotating 35°	0.0923
Blurring	0.6192

Table2: Comparison between extracted watermarks using SF

III. Result and discussion

In this paper we discuss watermarking process in two frequency domain DCT and FFT we notice that the process is the same but we apply different transformation, we can also note that both methods have the same robustness for all types of attack except blurring we can notice that FFT is robuster than DCT.

IV. Conclusion

In this one we have a general definition of digital image watermarking, our own work in watermarking starts in chapter two using DWT first we decompose the host image into four bands LL, LH, HL and HH and we embed the watermark in each band and with different values of QF and embedding factor we note that at QF=100 and alpha=0.09 we can retrieve the watermark image with SF=1; Figure 6 show watts

By applying different types of attacks to the watermarking image embedded in the LL band, we record the result in Figure 8 and note the effect of each type.

In chapter three and four we analyze watermarking mechanism in two frequency domain DCT and FFT we note that the procedure is the same but we implement different transformation, we can also find that the two approaches have the same robustness for all attack forms except that we can say that FFT is more robust than DCT.

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