Comparative Analysis of Wavelet Domain Techniques for Image Steganography

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Abstract: **It is now becoming increasingly well known that signal and image processing are getting great improvements in performance by using various wavelet based methods. In order to achieve better understanding of wavelet based methods, Haar , daubechies, symlet, and Biorthogonal wavelets are discussed. Image is decomposed into four sub bands using DWT. Secret image is hidden by alpha blending technique in the corresponding sub bands of the original image. During embedding, secret image is dispersed within the original image depending upon the alpha value. Extraction of the secret image varies according to the alpha value.The proposed transforms are compared using different levels in DWT based image steganography by using statistical parameters such as peak-signal-to-noise-ratio (PSNR) and mean square error (MSE). The experimental results demonstrate that the watermarks generated with the proposed algorithm are invisible and the quality of watermarked image and the recovered image are improved.**

Keywords– **Wavelet , Haar,Biorthogonal, db, symlet, alpha blending.**

I.INTRODUCTION

Steganography [1, 2, 3] is the process of hiding of a secret message within an ordinary message and extracting it at destination. Any other person viewing the message will fail to know that it contains secret/encrypted data. The word steganography comes from the Greek word “steganos” which means “covered” and “graphei” meaning “writing”.

Converting image from one format to another format and back could destroy information secret in LSB’s. Stego-images can be easily detected by statistical analysis like histogram analysis. This technique involves replace N (least significant bit of each pixel of a container image) with the data of a secret message. Stego-image gets destroyed as we increase N . In frequency domain, we can hidedata by using Discrete Cosine Transformation (DCT) [4]. The limitation of this approach is blocking artifact. Grouping the pixel into 8x8 blocks and then transforming the pixel blocks into 64 DCT co-efficient each. Any modification of a single DCT co-efficient will affect all 64 image pixels in that block. Discrete Wavelet Transformation (DWT)approach [5]is one of the modern techniques of Steganography. In the Discrete Wavelet Transform spread spectrum based approach, here binary secret images are dispersed within selective sub-bands using a pseudo-random sequence and a session based key **.**

Wavelets are mathematical functions that divide data into different frequency components, and then study each and every component with a resolution matched to its scale. They have various advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. Wavelets were developed independently in the fields ofelectrical engineering, seismic geology, mathematics and quantum physics. Interchanges between these fields during the last ten years have led to many new wavelet applications such as human-vision,image compression, radar, turbulence and earthquake prediction.

II. DISCRETE WAVELET TRANSFORMATION

The wavelet transformation describes a multi-resolution decomposition process in terms of expansion of an Image onto a set of wavelet basis function. Discrete Wavelet Transformation (DWT) having its own excellent space frequency localization properly. Applying DWT in 2D images corresponds to 2D filter image processing in each dimension. The input image is divided into 4 non-overlapping multi-resolution sub-bands by the filters, namely (LL1), (LH1), (HL1) and (HH1). The sub-band (LL1) is further processed to obtain the next coarser scale of wavelet coefficients, until some final scale “N” is reached. When “N” is reached, we’ll have 3N+1 sub-bands consisting of the multi-resolution sub-bands (LLN) and (LHX), (HLX) and (HHX) where “X” ranges from 1 until "N". Generally most of the Image energy is stored in these sub-bands.

Discrete wavelet transform (DWT) have certain properties that makes it better choice for image compression. DWT is especially suitable for images that have higher resolution. It possesses the property of Multi-resolution i.e., it represents image on a different resolution level simultaneously [6]. The resolution is determined by a threshold below which all fluctuations or details are ignored. Due to higher decor -relation property, DWT can provide higher compression ratios and better image quality [7]. DWT offers adaptive spatial-frequency resolution (better spatial resolution at high frequencies and better frequency resolution at low frequencies). Therefore, DWT are potentiality for good representation of image with fewer coefficients [5]. DWT Converts an input series into one low-pass wavelet coefficient series and one high-pass wavelet coefficient series (each of length n/2) given by:

$H1= x2i-1\ Y-1\ M=0\ Sm$(Z) (a)

$L1= x2i-1\ Y-1\ M=0\ tm$(Z) (b)

Where $Sm\ (Z)$and$tm\ (Z)$ are called wavelet filters, Y is the length of the filter, and i = 0, ($n2$ -1). In practice (a) and (b) is applied recursively on the low-pass series until a desired number of iterations are reached.

To perform third level decomposition, we apply DWTagainto LL2 band which decompose this band into the four sub-bands – LL3, LH3, HL3, HH3. This results in total 10 sub-bands per component. LH1, HL1, and HH1 contain the highest frequency bands present in the image tile, while LL3 contains thelowest frequency band. The three-level DWT decomposition is shown as in Fig.1

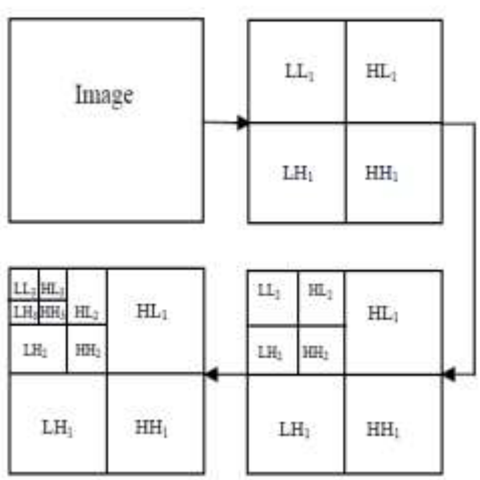

Figure 1. 3-Level discrete wavelet decompositions

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III. ALPHA BLENDING TECHNIQUE

It is away of mixing the two images together to form a final image. Alpha Blending technique[8] can be accomplished in computer graphics by blending each pixel from the first source image with the corresponding pixel in the second source image.

The equation for executing the alpha blending technique is as follows,

Final image's pixel = alpha * (First image's source pixel) +
(1.0-alpha) * (Second image's source pixel)

The blending factor or percentage of colors from the first source image used in the blended image is called the "alpha." The alpha value used in algebra is in the range 0.0 to 1.0, instead of 0 to 100%.

Alpha-blending blind Image hiding technique to generate Stego image is given by

Stego Image Embedding:

SII=alpha*(CI) + (1.0-alpha)*(SI) (1)

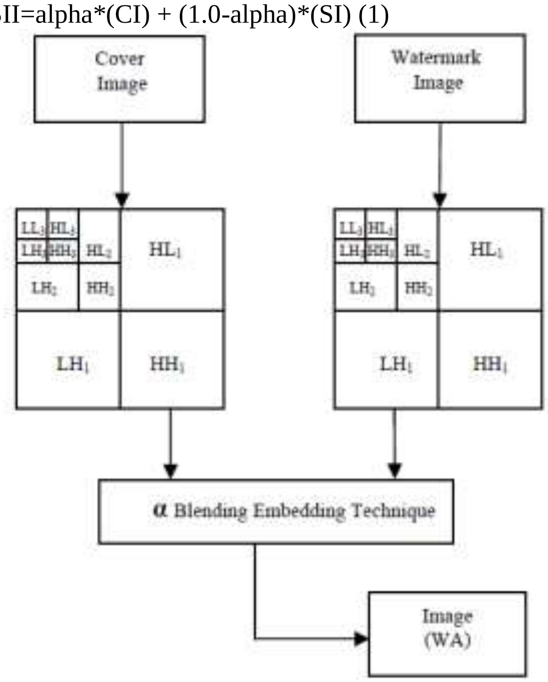

Figure 2: watermark embedding technique

Stego Image Extraction:

RSI= (SII - alpha*CI) (2)

Where, RSI=Recovered Stego Image, SII=Stego image, CI= selected sub-band of the cover image, SI= selected corresponding sub-band of the secret image.

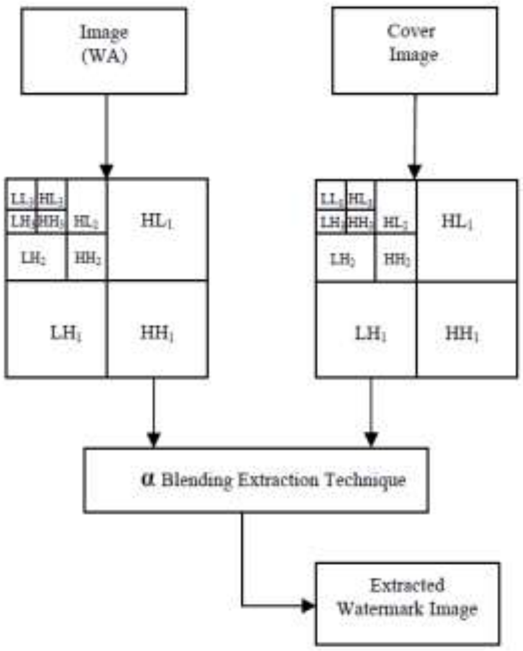

Figure 3: watermark extraction technique

IV. HAAR WAVELET

Any discussion of wavelets begins with HAAR wavelet [9], the first and simplest. HAAR Transform is orthogonal and real, results in a very fast transform [10]. HAAR wavelet is discontinuous, resembles a step function and represents the same wavelet as Daubechies db1. It is memory efficient, fast and exactly reversible without the edge effect [10]. The most distinctive feature of HAAR Transform lies in the fact that it lends itself easily to simple manual calculations.

For an input, represented by a list of numbers, the HAAR wavelet may be considered to simply pair up the input values, storing the difference and then passing the sum. This process is repeated recursively.
The Haar wavelet is the simplest wavelet transform. It is also the only symmetric wavelet in the Daubechies family and the only one that has an explicit expression in discrete form. Haar wavelets are related to a mathematical operation called Haar transform, which serves as a prototype for all other wavelet transforms[11]. Like all wavelet trans-forms, the Haar transform decomposes a discrete signal into two subsignals of half its length. One subsignal is a running average or trend, and the other subsignal is a running difference or fluctuation[12]. The Haar wavelet transform has the advantages of being conceptually simple, fast and memory efficient, since it can be calculated in place without a temporary array. Furthermore, it is exactly reversible without the edge effects that is the problem of other wavelet transforms. On the other hand, the Haar transform has its limitations because of its discontinuity, which can be a problem for some applications, like compression and noise removal of audio signal processing.

During computation, the analyzing wavelet is shifted over the full domain of the analyzed function. The result of DWT is a set of wavelet coefficients, which measure the contribution of the wavelets at the locations and scales.

The Daubechies wavelet transforms are defined in the same way as the Haar transform by computing the running averages and differences via scalar products with scaling signals and wavelets.

V. BIORTHOGONAL WAVELET TRANSFORM

It is well known that bases that span a space do not have to be orthogonal. In order to gain greater flexibility in the construction of wavelet bases, the orthogonality condition is relaxed allowing semi-orthogonal, biorthogonal or non-orthogonal wavelet bases[13]. Biorthogonal Wavelets are the families of compactly supported symmetric wavelets. The symmetry of the filter coefficients is often desirable since it results in linear phase of the transfer function[13]. In the biorthogonal case, rather than having one scaling and wavelet function, there are two scaling functions that may generate different multiresolution analysis, and accordingly two different wavelet functions.
This family of wavelets exhibits the property of linear phase, which is needed for signal and reconstruction of image. By using two wavelets, one for decomposition (i.e., on the left side) and the other for reconstruction (on the right side) instead of the same single one, interesting properties are derived.
Analysis (decomposition) and synthesis (reconstruction) filter orders for Biorthogonal filters Specify the order of the analysis and synthesis filter orders for Biorthogonal filter banks as 1.1, 1.3, 1.5, 1.7, 2.2, 2.4, 2.6, 3.1, 3.3, 3.5, 3.9, 4.4, or 5.5, 6.8. [14] Unlike orthogonal wavelets, Biorthogonal wavelets require 2 different filters one for the analysis and other for synthesis of an input. The first number is order of the synthesis filter while th second number is the order of the analysis filter.
The dual scaling and wavelet functions have the following properties:
1. They are zero outside of a segment.
2. The calculation algorithms are maintained, and thus are very simple.
3. The associated filters are symmetrical in nature.
4. The functions used in the calculations are

easier to build numerically than those used in theDaubechies wavelets.

VI. DAUBECHIES WAVELET

This wavelet is similar tohaar wavelet but different in defining scaling signals and wavelets. It uses overlapping windows, so the high frequency coefficient spectrum reflects all high frequency changes.

Ingrid Daubechies, one of the brightest stars in the world of wavelet research, invented what are called compactly supported orthonormal wavelets -- thus making discrete wavelet analysis practicable.

The names of the Daubechies family wavelets are written as dbN, where N is the order, and dbis the "surname" of wavelet. The db1 wavelet, as mentioned above, is the same as Haar wavelet.

The support length of wavelet is 2N - 1. The number of vanishing moments of is N.

Most dbN are not symmetrical. For some, the asymmetry is very pronounced.

The regularity increases with the order. When N becomes very large, and belong to where μ is approximately equal to 0.2. Certainly, this asymptotic value is too pessimistic for small-order N. Note that the functions are more regular at certain points than at others. It is energy preserving wavelet.

The analysis is orthogonal.

VII. SYMLET WAVELET

Daubechies proposes modifications of her wavelets such that their symmetry can be increased while retaining great simplicity. It is modified version of Daubechies wavelet with increased symmetry. It is same as dbn. In symN, N is the order. Some authors use 2N instead of N. Symlets are only near symmetric; consequently some authors do not call them symlets.

Symletwavelet are compactly supported orthogonal. Arbitrary number of vanishing moments are present. It has arbitrary regularity.

VIII.RESULTS AND ANALYSIS

Different wavelet families are present on which alpha blending technique is implemented. Alpha blending technique contains two constants (alpha) and (1-alpha), meaning the sum of these two is 1. Here two constants ‘k’ and ‘q’ in place of alpha and (1-alpha) are taken and keeping value of ‘k’ constant , by changing values of ‘q’ such that their sum has 5 different values as {0.8, 0.9, 1, 1.1, 1.2} and it results PSNR for both stego image and recovered image is maximum when there sum is 1and MSE value is minimum when sum is taken as 1.

First of all DWT is applied on image and then using alpha blending technique simulation result is obtained. Figure 4 shows the original cover image and image to hide.

Figure 4: Cover Image and Image to hide

All these results are performed and simulated in MATLAB (R2007b version 7.5).

Figure 5: Cover Image and Stego Image

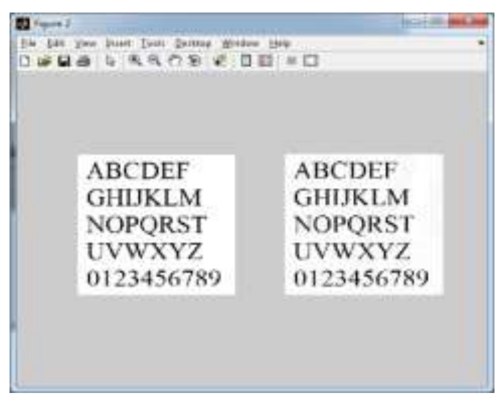

Figure 6: Image to hide and Recovered image

When k = 0.95 , q = 0.05 , k+q = 1

	LEVEL1	LEVEL2	LEVEL3	LEVEL4	LEVEL5	LEVEL6
HARR **	35.775	35.7992	35.8012	35.8019	35.802	35.802
DB8 **	35.5259	35.5477	35.5666	35.6101	35.6373	35.6826
BIOR4.4	35.2926	35.2576	35.2252	35.1889	35.1678	35.1382
SYM	35.4219	35.4529	35.4597	35.4734	35.5068	35.6044
AVERAGE	35.50385	35.51435	35.51318	35.51858	35.52848	35.5568

Table 1: PSNR for recovered image

****** means more PSNR value than average or better than average

	LEVEL1	LEVEL2	LEVEL3	LEVEL4	LEVEL5	LEVEL6
HARR	31.0393	31.0385	31.0384	31.0383	31.0383	31.0383
DBB **	31.0528	31.0526	31.0523	31.0513	31.0511	31.0499
BIOR4.4 **	31.0567	31.0573	31.0579	31.059	31.0591	31.0597
SYM **	31.0545	31.0538	31.0546	31.0547	31.0538	31.052
AVERAGE	31.05083	31.05055	31.0508	31.05083	31.05058	31.04998

Table 2: PSNR for stego image

****** means more PSNR value than average or better than average

	LEVEL1	LEVEL2	LEVEL3	LEVEL4	LEVEL5	LEVEL6
HARR ##	17.2021	17.1064	17.0987	17.0957	17.0955	17.0955
DB8 ##	18.2174	18.1265	18.0478	17.8677	17.756	17.5719
BIOR4.4	19.2228	19.3786	19.5238	19.6876	19.7835	19.9187
SYM	18.6592	18.5266	18.4974	18.439	18.298	17.8911
AVERAGE	18.32538	18.28453	18.29193	18.2725	18.23325	18.1193

Table 3: MSE for recovered image

means less MSE value than average or better than average

	LEVEL1	LEVEL2	LEVEL 3	LEVEL4	LEVEL5	LEVEL6
HARR	51.1858	51.1958	51.1969	51.1974	51.1975	51.1975
DB8 ##	51.0266	51.0296	51.0326	51.0443	51.0473	51.0609
BIOR4.4 ##	50.9811	50.9747	50.9668	50.9547	50.953	50.946
SYM	51.0076	51.0157	51.0061	51.0049	51.0153	51.0362
AVERAGE	51.05028	51.05395	51.0506	51.05033	51.05328	51.06015

Table 4: MSE for stego image

means less MSE value than average or better than average

By finding average values of all the four families we see that DB8 has more PSNR value than the average one in both cases i.e. stego image and recovered image and less MSE value than average. Therefore, DB8 is the best method to be chosen when we compare both stego and recovered image.

IX. CONCLUSION

Results shows that in case of stego image PSNR and MSE values of BIORTHOGONAL are best and of HAAR are worst, but in case of recovered image PSNR and MSE values of HAAR are best and of BIORTHOGONAL are worst.

At values k+q=1, best result tables are found of both PSNR and MSE. So, by calculating average of these tables' values , the family which is providing best overall results is found.

By finding average values of all the four families, different families shows different values, one shows more value than average in one case while less than average in other. But, out of these four families DB8 has more PSNR value than the average one in both cases i.e. stego image and recovered image and less MSE value than average. So from results it is concluded that DB8 is providing best results when we consider both stego and recovered image.

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