4.1 Introduction

As discussed in chapter 3, watermarking schemes based on SVD alone are not robust to attacks therefore SVD is combined with other transformation mostly with DWT for implementing good watermarking schemes [48] and [72]. From literature, comparative analysis of different watermarking techniques, which uses different domains for watermark embedding has their own merits and demerits.

The proposed method considered as transform domain method as it is observed that transform domain methods are specifically better than spatial domain method, for both reasons of robustness and visual quality. Compared to earlier approaches mentioned in literature, it had been seen that individual DWT based technique is better in perceptibility while SVD based technique is better in robustness. It has also been observed that SVD and DWT based techniques can be used to embed both binary and grayscale images whereas the previous techniques were able to embed only binary data [75], [88], [112], [119] and [126]. In this method, hybridization of the two approaches namely DWT and SVD is done to hide the color watermark in color image so as to get highly perceptible watermarked image.

A brief description of wavelets, DWT and its role in the watermarking schemes has been presented and then proposed algorithms with results are discussed.

4.2 WAVELET

The next form of representing the signal is the transform of a signal. The transform does not change the information content present in the signal. Basically wavelet transform is used to analyze non-stationary signals whose frequency response varies in time, as Fourier Transform (FT) is not suitable for such signals [17], [53] and [122]. Fourier Transform reveals the frequency composition of a signal as shown in Fig. 4.1. The wavelet transform provides a time-frequency representation of the signal [1], [61] and [66]. It was aimed to overcome the shortcoming of the STFT, which can also be used for analysis of non-stationary signals. While STFT gives a constant resolution at all frequencies the wavelet transform uses multi-resolution technique by which different frequencies are analyzed with different resolutions.
In STFT, the signal is divided into small segments, where these segments of the signal can be treated as stationary. For this, a window function is used and width of the window in time must be equal to the segment of the signal as shown in Fig. 4.2 (a) and (b).

The minor difference between FT and STFT is that in STFT, time-frequency response of a signal is obtained which is not possible with FT. But STFT failed to explain which spectral components exists at which instances of time. It presents only the
time intervals in which certain band of frequencies exists and is called resolution problem which can be solved with the selection of the width of the window function. If the window function is narrow, it gives the better time resolution but poor frequency resolution. If wider window is used, it provides good frequency resolution and poor time resolution. So wavelet transform has been developed as an alternate approach to STFT to overcome the resolution problem. The wavelet analysis has been done such that the signal is multiplied with the wavelet function to compute transform for various segments of the time domain signal at different frequencies. This approach is known as multi-resolution analysis (MRA), as it analyzes the signal at different frequencies giving different resolutions.

![Wave and Wavelet](image)

**Fig. 4.3:** Difference between Wave and Wavelet

![Wavelet Transform](image)

**Fig. 4.4:** Wavelet Transform representation

Wavelets are localized waves but wave is an oscillating function of space or time and is periodic as shown in Fig. 4.3. The energy of wavelets is concentrated in space and wavelets are well suited for the analysis of transient signals. While waves are used by STFT and Fourier Transform to analyze the signals and the Wavelet Transform uses wavelets of finite energy as shown in Fig. 4.4.
In wavelet analysis the multiplication of the signal to be analyzed with a wavelet function and then the transform is computed for each segment generated. A poor frequency resolution and good time resolution are given by the Wavelet Transform at high frequencies and also poor time resolution and better frequency resolution are given by the Wavelet Transform at low frequencies. Fig. 4.5 shows time-frequency response of a signal using STFT and DWT and Table 4.1 gives the comparison of mathematical forms of FT, STFT and WT.

![STFT and DWT Diagram]

Fig. 4.5: Time – frequency representation of STFT and DWT

### Table 4.1 Comparison of FT, STFT and WT

<table>
<thead>
<tr>
<th>Transformation</th>
<th>Representation</th>
<th>Result depends on parameters ($t, f, a, b$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fourier Transform</td>
<td>$X(\omega) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi \omega t} dt$</td>
<td>frequency ‘$f$’</td>
</tr>
<tr>
<td>STFT</td>
<td>$X(t, \omega) = \int_{-\infty}^{\infty} x(\tau) \phi(\omega - \frac{\tau}{a}) e^{-j2\pi \omega \tau} d\tau$</td>
<td>time ‘$t$’, frequency ‘$f$’</td>
</tr>
<tr>
<td>Wavelet Transform</td>
<td>$X(b, a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \phi(t - b) \left(\frac{t - b}{a}\right) dt$</td>
<td>Scaling ‘$a$’, translation ‘$b$’</td>
</tr>
</tbody>
</table>
4.2.1 Families of Wavelet

There are a number of basic functions that can be utilized as the mother wavelet for wavelet transformation [16] and [87]. Since all wavelet functions that are used in the transformation through scaling and translation are produced by the mother wavelet, the characteristics of the resulting Wavelet Transform are determined. Hence, the details of the selected application should be taken into consideration and the appropriate mother wavelet should be selected in order to use the Wavelet Transform effectively.

Some of the commonly used wavelet functions are shown in Fig. 4.6 to 4.9. Haar wavelet is one of the oldest and simplest wavelet, therefore any wavelet discussion starts with the Haar wavelet. It is a bipolar step function. Like all wavelet transforms, the Haar transform decomposes a discrete signal into two sub signals of half its length. One sub-signal is a running average or trend; the other sub-signal is a running difference or fluctuation.

The Haar wavelet transform has a number of advantages:

- It is conceptually simple
- It is fast
- It is memory efficient, since it can be calculated in place without a temporary Array
- It is exactly reversible without the edge effects that are a problem with other Wavelet transforms

Haar wavelet is a real function and anti-symmetric with respect to \( t=1/2 \). It is discontinuous in time, therefore not differentiable and is localized in the time domain. But it has poor localization in the frequency domain.

The most popular wavelets are Daubechies wavelets. They are used in numerous applications and they represent the foundations of wavelet signal processing. The Daubechies wavelet bases are a family of orthonormal, compactly supported scaling and wavelet functions that have maximum regularity for a given length of the support of the quadrature mirror filters. As their frequency responses have maximum flatness at a range of frequencies, they are also called Maxflat wavelets. This is a very optable property in
few applications. Orthogonal wavelets support compactly the Haar, Daubechies, Symlets and Coiflets.

The wavelets are chosen by considering their ability and shape to analyze the signals in a selected application. Some of the wavelet families are described here:

1. Haar wavelet

General characteristics: Orthogonal,

Support width: 1

Filters length: 2

Number of vanishing moments for $\psi$: 1

Scaling function: yes

2. Daubechies family

General characteristics: Order $N = 1,...$

Orthogonal

Support width: $2N - 1$

Filters length: $2N$

Number of vanishing moments for $\psi$: $N$

Scaling function: yes
3. Coiflet family

General characteristics: Order $N = 1, \ldots, 5$

Orthogonal

Support width: $6N - 1$

Filters length: $6N$

Symmetry near from

Number of vanishing moments for $\psi$: $2N$
4. Meyer wavelet

General characteristics: Orthogonal

Compact support: no

Effective support: \([-8, 8]\)

Symmetry: yes

Scaling function: yes

![Scaling function and Wavelet function](image)

**Fig. 4.9: Meyer**

### 4.2.2 Continuous Wavelet Transform

A continuous wavelet transform is used to divide a continuous-time function into wavelets. CWT has ability to construct a time frequency representation of a signal that offers very good time and frequency localization.

The CWT of one-dimensional signal \(x(t)\) is given by Eq. (4.1)

\[
W_{\psi, b}(a, t) = \frac{1}{\sqrt{|a|}} \int x(t) \psi^{*}\left(\frac{t-b}{a}\right) dt
\]  

--- (4.1)

Where a is a scaling parameter

b is a shifting parameter

\(\psi(x)\) is a mother wavelet or basis function
The shifting or translation parameter gives the time information in the wavelet transform which indicates the location of the window as it is shifted through the signal. The scaling parameter gives the frequency information in the wavelet transform.

The inverse one-dimensional continuous wavelet transform is given by Eq. (4.2) and Eq. (4.3).

\[ x(t) = \frac{1}{C_{\psi}} \int_{-\infty}^{\infty} W(t, b) \psi_{a,b}(\frac{t-b}{a^2}) da \]  
\[ \text{Eq. (4.2)} \]

Where

\[ C_{\psi} = \int_{-\infty}^{\infty} \left| \psi(\omega) \right|^2 d\omega < \infty \]  
\[ \text{Eq. (4.3)} \]

The wavelet transform of a signal using CWT is obtained by changing the scale of the analysis window, shifting the window in time, multiplying the signal and integrating the result over all time. Equations (4.4) to (4.6) describing the conditions for the properties of wavelets used in continuous wavelet transform are followed as:

A wavelet \( \psi \) is simply a function of time \( t \) that obeys a basic rule, known as the wavelet admissibility condition:

\[ C_{\psi} = \int_{0}^{\infty} \left| \hat{\psi}(\omega) \right|^2 d\omega < \infty \]  
\[ \text{Eq. (4.4)} \]

Where \( \hat{\psi} \) is the Fourier transform. This condition ensures that \( \hat{\psi} \) goes to zero quickly as \( \omega \rightarrow 0 \). In fact, to guarantee that \( C_{\psi} < \infty \). And the condition imposed is

\[ \int_{-\infty}^{\infty} \psi(t) dt = 0 \]  
\[ \text{Eq. (4.5)} \]

A secondary condition imposed on wavelet function is unit energy that is gives by

\[ \int |\psi(t)|^2 dt = 1 \]  
\[ \text{Eq. (4.6)} \]
4.2.3 Discrete Wavelet Transform

In mathematics, a wavelet series is the best representation of a square integrable (real or complex valued) function by certain orthonormal series generated by a wavelet. The wavelet transform can provide the frequency of the signals and the time associated to those frequencies, making it very convenient for its application in numerous fields.

In numerical analysis and functional analysis, a discrete wavelet transform (DWT) is used for discrete sampling of a signal. A key advantage of it over Fourier transforms is temporal resolution: it captures both frequency and location information (location in time). The discrete wavelet transform has a huge number of applications in science, engineering, and mathematics and computer science. Most notably, it is used for signal coding, to represent a discrete signal in a more redundant form, often as a preconditioning for data compression.

In most of the applications that includes the field of image processing, the wavelet transform has very important contributions to make the application smooth and fruitful. Compression, signal analysis, digital watermarking and signal processing like some of the applications made it practical in this field of study in the past few decades. Waves are periodic in nature and are oscillating with respect to time or space.

On the other side wavelets are localized waves with its energy concentrated in time or space and they are used for the purpose of analyzing a signal. Actually the Discrete Wavelet transform does the convolution operation between the 1D or 2D signals with particular instances of wavelets at various time scales and positions. The DWT [35], [45], [108] and [110] is based on sub-band coding, is easy to implement, does require limited time and resources and yields fast computations.

The DWT is a combined process of filtering and sub-sampling where sub-sampling can be up-sampling or down-sampling. Filtering operation determines the resolution, known to be a measurement about how much information the signal does contain while sub-sampling operation determines the scale of the signal.

A series of successive low pass filter $h_l[m]$ and high pass filter $h_h[m]$ are used to compute multi-level DWT as shown in Fig. 4.10. At each decomposition level, frequency resolution is doubled as the uncertainty in frequency is reduced by half and
time resolution is made half means if the signal has originally of 500 samples it reduces to 250 samples at the end of first decomposition level. So one of the beautiful observations is that at high frequency very good time resolution where as at low frequencies good frequency resolution is observed.

Fig. 4.10: Discrete wavelet transformation representation

To understand the basic idea of the DWT, consider the one dimensional signal. The signal is passed through a low pass filter and a high pass filter so as to get both high and low frequency parts of the signal. High frequency part contains edge components whereas low frequency part contains smooth region of components.

The same process is repeated for the low frequency part so as to get second level low and high frequency components. The number of decomposition levels depends on the application of interest. So far as watermarking and compression is concerned a maximum of five levels of decomposition are computed. The original signal can also be reconstructed from the knowledge of DWT coefficients. This process of reconstruction (synthesis) is called the inverse DWT (IDWT).
Any signal that contains its most important and informative part in its low-frequency component and that is the reason why low frequency components are very important, on the other hand, the high frequency components are of less importance. Consider the human voice, if high frequency components are removed from a song it would sound different, but one can still identify the saying. However, if low-frequency components are removed, one would be able to hear garbage only.

In wavelet analysis two words are frequent i.e. approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. Fig. 4.11 shows the first stage of the decomposition wherein signal is applied to low pass and high pass filters.

If the original signal is of size 1x1000 then size of each of the approximation and detail component would be 1x1000. So the output contains twice the samples compare to input. So output of both the filters is down sampled by 2, so that each of the output would have half the size of the original signal and hence the total size equals to that of the original signal. Fig. 4.12 shows the concept of down sampling after filtering. The decomposition or analysis process with down sampling produces the same number of approximation and detail coefficients.
Fig. 4.12: Analysis with down sampling

For a two dimensional image $f(x,y)$, the forward and reverse decomposition can be done by applying DWT and IDWT. These operations are performed first on dimension $x$ and then the same process can be performed for the other dimension $y$. This kind of 2-D DWT decomposes the image into four parts namely approximation components, Horizontal Detail components, Vertical Detail Components and Diagonal Detail Components as shown in Fig. 4.13 and 4.14. The approximation components of the DWT contain most significant information of the image. And the other detail coefficients hold the horizontal, vertical and diagonal information of an image as shown in Fig. 4.15. Any disturbance to approximation coefficients of DWT influences the visual perception of the image. Therefore for processing of an image using DWT, detail coefficients are most preferred instead of approximation components.

Fig. 4.13: DWT decomposition of a 2-D image
Fig. 4.14: Basic decomposition steps for image analysis

The example for wavelet decomposition with Lena image into four sub-band images is shown in Fig. 4.15.

Fig. 4.15: Lena image after wavelet decomposition
So, the wavelet transform is also called as joint time-frequency domain. The Wavelet transform decomposes a signal into a set of basis functions. These basis functions are called wavelets. The wavelet transform is computed separately for different segments of the time-domain signal at different frequencies [48]. The two level DWT decomposition is shown in Fig. 4.16 and an example with Lena image representation is shown in Fig. 4.17.

Mathematically, the DWT and IDWT can be stated as follows: To compute the wavelet transform of an image $f(x, y)$, a 2-dimensional scaling function $\phi(x,y)$ and three 2-dimensional wavelets $\psi^H(x,y), \psi^V(x,y), \psi^D(x,y)$ that are computed using Eq. (4.7) through Eq.(4.10) respectively [41] and [48].
\[ \phi(x, y) = \phi(x) \phi(y) \]  
\[ \psi^H(x, y) = \psi(x) \phi(y) \]  
\[ \psi^V(x, y) = \phi(x) \psi(y) \]  
\[ \psi^D(x, y) = \psi(x) \psi(y) \]

In Eq. (4.8), Eq. (4.9) and Eq. (4.10), wavelet functions measure the intensity variation for images along columns i.e. horizontal edges, along rows i.e. vertical edges and along diagonals respectively.

It is clear from Eq. (4.7) through Eq. (4.10) that in order to compute 2-dimensional scaling and wavelet function, product of 1-dimensional scaling and wavelet functions is used that is computed using Eq. (4.11) and Eq. (4.13) respectively.

\[ \phi_{j,k} = 2^j \phi \left( x - \frac{k}{2^j} \right) \]  
\[ \psi_{j,k} = 2^j \psi \left( x - \frac{k}{2^j} \right) \]  

Where \( j, k \in \mathbb{Z} \), \( k \) determines the position of \( \phi_{j,k} \) along the x-axis and \( j \) determines the width of \( \phi_{j,k} \). The value of scaling function \( \phi(x) \) of Haar Wavelet is computed using Eq. (4.12).

\[ \phi x = 1, \quad 0 \leq x < 1 \]
\[ 0, \quad \text{otherwise} \]

Similarly wavelet function is defined using Eq. (4.13).

\[ \psi_{j,k} = 2^j \psi \left( x - \frac{k}{2^j} \right) \]

Where \( \psi(x) \) is defined by using Eq. (4.14).

\[ \psi(x) = \begin{cases} 1 & 0 \leq x < 0.5 \\ -1 & 0.5 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases} \]  

Using the scaling and wavelet function defined in Eq.(4.11) and Eq.(4.13), DWT of an image of size \( MN \) is defined using Eq. (4.15) and Eq. (4.16) respectively.
\[
W_\phi(0,m,n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \tilde{\phi}_{j_0,m,n} \quad (4.15)
\]

\[
W_i^j(0,m,n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \tilde{\psi}_{j,m,n} \quad (4.16)
\]

Where \(i = \{H, V, D\}\) defines intensity variation along horizontal, vertical and diagonal direction

\(j_0\) is an arbitrary starting scale

\(W_\phi(0,m,n)\) coefficients define an approximation of an image function \(f(x, y)\) at scale \(j_0\) and

\(W_i^j(0,m,n)\) coefficients define horizontal, vertical and diagonal details for scale \(j \geq j_0\).

As shown in Fig.4.15, four sub bands LL, HL, LH and HH are generated after applying 1-level two dimensional DWT on input image. From the given DWT function, image function \(f(x, y)\) can be computed by applying Inverse Discrete Wavelet Transform (IDWT) using Eq. (4.17).

\[
f(x,y) = \frac{1}{\sqrt{MN}} \sum_{m} \sum_{n} W_\phi(0,m,n) \tilde{\phi}_{j_0,m,n} + \frac{1}{\sqrt{MN}} \sum_{(j_0)} \sum_{m} \sum_{n} W_i^j(0,m,n) \tilde{\psi}_{j,m,n} \quad (4.17)
\]

DWT performs Multi Resolution Analysis (MRA) i.e. it analyzes the signal at different frequencies giving different resolutions. MRA is designed to give good time resolution and poor frequency resolution at high frequencies. At lower frequencies it gives good frequency resolution and poor time resolution. DWT is good for signal having high frequency components for short duration and low frequency components for long duration like images and video frames.
4.3 Advantages of DWT in Watermarking

The watermarking in wavelet domain [87] is preferred as it has many advantages as under:

- Complex values representing the signal in the time domain are transformed into complex values representing the signal in time-frequency domain.

- Adequate for representing transient signals with non-stationary frequency characteristics.

- The number of samples N must be an integer power of 2, so the FFT algorithm can be used to speed up computations.

- High data compression is possible with wavelets.

- Wavelets can show an image at various levels of resolution and they can be sequentially process from low resolution to high resolution as Wavelet-based watermarking techniques have multi-resolution hierarchical characteristics.

- The high frequency sub-bands of the wavelet transform contains the edges and textures of the image and the human eye is not usually very sensitive to changes in such bands. This makes the watermark to be added to such sub-bands without being perceived by the human eye.

- High robustness to common signal processing.

- DWT-based watermarking techniques support high capacity.

- DWT allows watermark to be inserted in both local region and global region of the image due to which it is robust against scaling and cropping.

- The HVS is more closely understood by wavelet transform than the DCT.

- Watermark information can be evenly distributed in original image using DWT.

- DCT and DFT are full frame transforms and hence any change in the transform coefficients affects the entire image.
However, DWT has spatial frequency locality, which means if signal is embedded it will affect the image locally. Hence, both the frequency and spatial description for an image are provided by a wavelet transform.

4.4 Proposed Color Image Watermarking

The proposed scheme embeds the color watermark into color cover image [99], [115]. The color image is represented by Red (R), Green (G) and Blue (B) channels. Out of these three channels, change in the intensity of R channel is the most sensitive to human eyes whereas for B channel it is least sensitive. Hence, in the proposed scheme the blue channel is considered for embedding. The wavelet transform of image gives four frequency sub-band coefficients. In image processing each sub-band is resistant to different types of attacks or transformations. For example, the low frequency sub-band coefficients are less robust to geometrical distortions and histogram equalization.

In the proposed scheme the copy of the watermark is embedded into three sub-band coefficients where it is hard to destroy the watermark even after applying the different types of attacks on the watermarked images. To improve the robustness of the scheme the watermark is embedded into different sub-band coefficients obtained from B channel of the color image.

The proposed method uses the color image I of size m x n as the host image and the color/monochrome image W of size m/2 x n/2 as the watermark. The color image is transformed into R, G and B planes of size m x n. As human eye is less sensitive to change in the intensity of the B plane, it is chosen for watermark embedding. Then two-level DWT is applied on the B plane to generate sub-band coefficients LL, LH, HL, HH of size m/2 x n/2. The SVD decomposition is applied on detail sub-band coefficients and R, G, B planes of watermark. The singular values of three planes of watermark are added to the sub-bands (LH, HL, HH) of the DWT transformed B plane using scaling factor a. Block diagram for embedding process is shown in Fig. 4.18.
Fig. 4.18: Block diagram for watermark embedding based on DWT-SVD

Now the inverse DWT is applied on the modified sub-band coefficients of B plane to achieve the embedded B plane. The embedded B plane is combined with R and G planes of host image to achieve watermarked color image. As non-blind watermarking technique uses the host image and watermark image to extract the Watermark, this extraction process uses the host image $I$, watermarked color image $I_l$ each of size $m \times n$ and the watermark image $W$ of size $m/2 \times n/2$. The original and the watermarked color images are transformed into R, G and B planes. On the B plane of the image, DWT is applied to create sub-band coefficients LL, LH, HL, HH of size $m/2 \times n/2$. The SVD decomposition is applied to LH, HL, HH sub-bands.
The singular values of R, G, B planes of watermark are extracted from the LH₁, HL₁, HH₁ of the DWT transformed B plane of color image and watermarked color image using scaling factor a. The extracted singular values of watermark are combined with orthogonal matrices of watermark to generate the watermark image. Block diagram for watermark extraction is displayed in Fig. 4.19.
4.4.1 Proposed Color Image Watermark Embedding Algorithm

The two inputs to the embedding algorithm are of RGB color images and let the size of the host image is m x n and watermark is m/2 x n/2.

1. Segregation of R, G, B planes from host color image
2. Apply Haar wavelet to the B plane of host image to decompose it into four sub bands LL, LH, HL and HH.
3. SVD is applied on LH, HL and HH bands to provide singular values
4. Separation of R, G, B planes from watermark image
5. Apply SVD to the three planes of watermark image i.e R, G, B
6. Modify the LH, HL, HH band coefficients with the singular values of R, G, B planes of watermark image and inverse SVD is employed
7. Apply Inverse DWT on LL and modified LH, HL, HH bands to get watermarked B plane
8. Convert watermarked B plane along with R and G planes into color image to display watermarked image

The output of the proposed algorithm is a watermarked color image which is visually same as the host color image with null degradation.

4.4.2 Proposed Color Image Watermark Detection Algorithm

The inputs to the watermark detection algorithm are watermarked color image with and without distortions, unmarked original image and singular vectors of watermark image.

1. Separate the watermarked image into R G B planes
2. Employ DWT on the B plane of watermarked image
3. Apply SVD to the LH, HL, HH sub-bands to get singular values
4. Obtain the singular matrices of R, G, B planes from the singular values of watermarked B plane produced in above step and the singular values of original image.

5. R, G, B planes of watermark image are produced by applying Inverse SVD with the help of orthogonal vectors of watermark planes

6. Amalgamate the R, G, B planes to detect hidden watermark image

The output of this detection algorithm is color watermark image without any loss of color information which is similar to the actual inserted color watermark. The detection algorithm is performed on attacked color watermarked image. The same algorithm is tested at various scaling factors to obtain the distortion less output with tolerable perceptual quality and robustness.

4.5 Performance Evaluation of DWT-SVD based Color Image Watermarking

This scheme hides the color watermark into color host image using the watermark embedding and extraction algorithms given in section 4.3. Here Peppers image is used as the original color image and SNIST logo is chosen as color watermark image.

4.5.1 Analysis of experimental results

The present watermarking algorithm is tested on different original images at various scaling factors. The scaling factor is set according to the quality of recovered watermark image and watermarked image. Greater values of scaling factor causes better detection of watermark but reduce the overall quality of image. Here the original color image is of size 256 X 256 and watermark color image of size 128 X 128. The embedding of color logo in color host image and detected watermark are shown in Fig. 4.20. PSNR values are evaluated to measure the imperceptibility and robustness is also observed to estimate the quality of identified watermark. The correlation factor found to be unity as the watermarked image is not exposed to any kind of distortion.
Fig. 4.20: Results of color watermarking (a) Peppers image embedded with color logo and (b) Extracted watermark

The following figures show input host image, separated B plane, watermark image, decomposed B-plane, watermarked B-plane, watermarked image, extracted watermark, attacked watermarked image and retrieved watermark from attacked images.

The effect of Salt & Pepper noise on watermarked color image at scaling factor of 0.01 is shown in Fig. 4.21, where it has been observed that the retrieved watermark is highly distorted. The same effect at scaling factor of 0.5 is shown in Fig. 4.24, that is due to the embedding of watermark color information in decomposed blue plane only. Though the retrieved watermark logo is quite detectable, the presence of more noise is observed at lower values of scaling factor.

The individual planes of host image and that of watermarked blue channel at scaling factor of 0.01 are shown in Fig. 4.22, where as individual planes of watermark image before and after noise attack are shown in Fig. 4.23. Similarly, the individual planes at scaling factor of 0.5 are shown in Fig. 4.25 and Fig. 4.26.
Fig. 4.21: Results of Salt & Pepper noise ($\alpha = 0.01$)

Fig. 4.22: Individual planes of host image and marked Blue channel without and with Salt & Pepper noise ($\alpha = 0.01$)
Fig. 4.23: Individual planes of watermark image without and with Salt & Pepper noise ($\alpha = 0.01$)

Fig. 4.24: Results of Salt & Pepper noise ($\alpha = 0.5$)
Fig. 4.25: Individual planes of host image and marked Blue channel without and with Salt & Pepper noise ($\alpha = 0.5$)

Fig. 4.26: Individual planes of watermark image without and with Salt & Pepper noise ($\alpha = 0.5$)

From Fig. 4.22 and 4.25, it has been observed that distortion in watermarked plane is reduced with increasing scaling factor from 0.01 to 0.5. Compared to retrieved watermark planes in Fig. 4.23 with those in Fig. 4.26, it has been viewed that the degradation of watermark is less at 0.5 scaling factor. However, the watermark is successfully detected, but its background color is affected.
Table 4.2 Performance metrics in terms of PSNR and MSE at different scaling factors

<table>
<thead>
<tr>
<th>Scaling Parameter</th>
<th>Images</th>
<th>MSE</th>
<th>PSNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>Peppers</td>
<td>0.1097</td>
<td>57.7293</td>
</tr>
<tr>
<td></td>
<td>Lena</td>
<td>0.1589</td>
<td>56.1184</td>
</tr>
<tr>
<td></td>
<td>Sunset</td>
<td>0.1500</td>
<td>56.3707</td>
</tr>
<tr>
<td></td>
<td>Balloon</td>
<td>0.1586</td>
<td>56.1282</td>
</tr>
<tr>
<td></td>
<td>Autumn</td>
<td>0.0909</td>
<td>58.5457</td>
</tr>
<tr>
<td>0.03</td>
<td>Peppers</td>
<td>0.5238</td>
<td>50.9390</td>
</tr>
<tr>
<td></td>
<td>Lena</td>
<td>0.9475</td>
<td>48.3652</td>
</tr>
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Therefore the PSNR value of watermarked image and CF value of extracted watermark are less under distortions. The performance metrics at various scaling factors for different images are shown in Table 4.1. Compared to all images, Autumn image offers highest PSNR value of 58.55 dB at scaling factor of 0.01 and Lena image gives 57.12 dB. But at unity scaling factor, Autumn image gives less value of 42.08 dB and least value proffered by Balloon image is 37.16 dB. The increased scaling factor produces large error between cover and watermarked images, thus the PSNR is reduced with increasing scaling factor from 0.01 to 1.

To maintain the tradeoff between imperceptibility and robustness, the range of scaling factor is optimized according to the perceptual quality of watermarked image and restored watermark. While scaling factor is 0.5, it seems to be a better choice to compromise imperceptibility and robustness. The algorithm is verified against various attacks by embedding SNIST logo into Peppers image and the estimated PSNR and CF values are shown in Table 4.2. The CF values found in Table 4.2 illustrate that the proposed algorithm is more resistant to Median filtering, Histogram equalization and Sharpening attacks.

Table 4.3 Performance metrics under various attacks

<table>
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<th>Attacks</th>
<th>Parameters</th>
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<tr>
<td>Histogram equalization</td>
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</tbody>
</table>

The PSNR values shown in Table 4.2 indicate the amount of distortion introduced by the attack. In rotation attack, less PSNR value specifies the minimum visual quality and the CF value represent the least robustness of the algorithm. This scheme performs well against median filtering compared to other attacks. From Table 4.2, it is observed that the PSNR value is high when the watermarked Peppers image is attacked by median filtering with 5x5 mask, as Median filter replaces each pixel value in
the image by the median of its neighborhood. And the CF value of the extracted watermark from the median filtered watermarked image using 5x5 mask is also high.

The effect of Gaussian noise with variance of 0.01 is shown in Fig. 4.27 and that of Median filtering on watermarked image with 5x5 mask is shown in Fig. 4.28.

Fig. 4.27: Results of Gaussian noise

Fig. 4.28: Results of Median filtering
Fig. 4.29: Results of Average filtering

Fig. 4.30: Results of Rotation
Average filtering impact on watermark image is shown in Fig. 4. 29 and the rotation of watermarked image by an angle of $10^0$ and its influence on extracted watermark is shown in Fig. 4. 30.

![Figure 1]

Fig. 4.31: Results of Histogram equalization

Histogram equalized watermarked image and its impact on watermark is shown in Fig. 4.31. From all the above distorted images, it can be noticed that the proposed scheme is efficiently detecting the presence of hidden watermark at scaling factor of 0.5 but the background of the extracted watermark is seriously affected under distortions.

From Table 4. 1, it can be seen that the imperceptibility of the image is far better than that of the previously discussed SVD based method. But when the watermarked image is suffered with image processing distortions like noise attacks, rotation and filtering attacks, it has been proved that this algorithm is successful in detecting the watermark but failed in retaining the color of extracted watermark under distortion. So, there is a possibility to further improve the quality of extracted watermark without losing color information even under presence of attacks.
4.5.2 Observations

Some of the observations are framed from the above results which are obtained by implementing the proposed watermark embedding and extraction algorithms. In this scheme scaling factor is chosen as 0.5 to get the tradeoff between required imperceptibility and robustness. CF measured between host and a watermarked image is unity at different scaling factors under no distortion.

- Blue plane of cover image is selected for embedding as this plane is least sensitive to human eye.

- Images with greater number of mid and high frequency transformed coefficients can hold the maximum watermark information.

- Greater values of scaling factor give high imperceptibility and poor robustness whereas decreased values of scaling factor provides less imperceptibility with improved acceptable robustness.

- Color of the watermark is retrieved without any degradation from undistorted watermarked image.

- Watermarking capacity is improved with this scheme based on the size of host and watermark images.

- Compared to SVD algorithm, great improvement in efficiency is observed in terms of PSNR whereas MSE decreases.

- From the discussions and results from the prior sections, it can be observed that this method is not capable of extracting the color of hidden image effectively when the watermark undergoes certain attacks.

- So robustness is poor in this proposed watermarking method.

- This scheme performs well for various formats of standard color test images compared to SVD based method.
4.6 Conclusion

This chapter describes the proposed method to embed color image watermark in transformed color host image using DWT and SVD domain. Since visual distortions are acceptable up to some extent, this algorithm is performed at various scaling factors to optimize the distortion less result. Invisibility and Robustness are measured objectively to compare with previous watermarking techniques. But when the watermarked image is suffered with image processing distortions like noise attacks, rotation and filtering attacks, it has been proved that this algorithm is successful in detecting the watermark but failed in retaining the color of extracted watermark under distortion. So, there is a necessity to restore the color of the watermark extracted from attacked watermarked media. To overcome the drawbacks, a novel hybrid image watermarking algorithm is explored in next chapter.