CHAPTER - III

**MIW with LWT-SVD**
3.1 Introduction

The chapter presents a hybrid algorithm for watermarking medical images with patient image as watermark. The algorithm is based on discrete wavelet transform with lifting scheme and singular value decomposition (LWT-SVD) for watermarking medical images.

In the previous chapter a 2D discrete wavelet transform (DWT) was used to embed the watermark patient image [9]. An appropriate dilation factor and filters were selected in the multiband wavelet transform to achieve better performance in terms of watermark invisibility and the robustness.

In a DWT-based scheme, the DWT coefficients are modified with the data that represents the watermark. Li et.al. [111] presented a hybrid scheme based on DWT and Singular Value Decomposition (SVD). After decomposing the cover image into four bands, SVD is applied to each band, and embed the same watermark data by modifying the singular values.

Modification in all frequencies allows the development of a watermarking scheme that is robust to a wide range of attacks [10]-[11]. Unlike the algorithms proposed by other researchers such as a DWT-SVD hybrid method to achieve the watermarking this chapter proposes LWT-SVD algorithm that possibly preserves the visual quality of watermarked medical images to a large extent.

This research proposes to use an amalgam of wavelet transform [18]-[19] and Singular Value Decomposition for medical image watermarking. Recently watermarking techniques have gone hybrid.
Hybrid watermarking schemes use mixture of two or three transformations in the watermarking process. SVD transform preserves minor transitions with largest changed singular values that occur during attacks. The basic process in DWT-SVD watermarking process lies in modifying the wavelet sub bands using singular values of binary watermark image[20]-[23].

A new improved watermarking scheme is proposed using lifting wavelet transform (LWT)[24] and SVD for medical images. The medical images of patients are watermarked with the image of that particular patient which is extracted at the doctor’s end for identification. Lifting wavelets have distinctive advantage that is explored and is missed in traditional wavelet transform.

With lifting wavelets the inverse transformation is undoing the operations of forward transform which reduce the artefacts during transformation. The rest of the chapter is organized as follows. Section 3.2 and 3.3 gives a brief introduction of lifting discrete wavelet transform and Singular Value Decomposition (SVD) techniques.

Section 3.4 deals with the process of medical image watermarking using LWT-SVD and section 3.5 the watermark extraction algorithm. Section 3.6 introduces measurable parameters that can judge the watermarking procedures along with results and discussion which provide insight into the use of hybrid multiresolution lifting wavelet transform and SVD for medical image watermarking. Finally conclusions are drawn on the medical image watermarking schemes using LWT-SVD technique in section 3.7.
3.2 Lifting Wavelet Transform (LWT)

Lifting wavelets come under the category of second generation wavelets that have distinctive advantages over traditional first generation wavelets. The lifting wavelets trim down the computing time and memory requirements as they adopt an in position realization of wavelet transform.

Unlike traditional wavelets the computations for lifting wavelets are performed in integer domain rather than real domain. More over the inverse process in lifting wavelets is renunciation of the processes performed during the forward transformation. This the main reason for choosing LWT[24] over traditional DWT for medical image watermarking. The Lifting Wavelet Transform (LWT) comprises of three basic steps which form the basis for integer transformations: split, predict and update as shown in figure 3.1.

![Figure 3.1: Lifting Wavelet Forward Transform](image)

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**Figure. 3.1:** Lifting Wavelet Forward Transform
Split — decompose the image \( I(x, y) \) into even \( I_e(x, y) \) and odd \( I_o(x, y) \) polyphase components. The z-Transform of even polyphase component is expressed as

\[
I_e(z_1, z_2) = \sum_{n=1}^{N} \sum_{m=1}^{M} I(2n_1, 2n_2) z_1^{-n_1} z_2^{-n_2}
\] (3.1)

and odd polyphase z-transform is expressed as

\[
I_o(z_1, z_2) = \sum_{n=1}^{N} \sum_{m=1}^{M} I(2n_1 + 1, 2n_2 + 1) z_1^{-n_1} z_2^{-n_2}
\] (3.2)

The combination of predict operation and subtraction replaces the odd poly-phase coefficient \( I_o(z_1, z_2) \) with difference between the odd poly-phase component \( I_o(z_1, z_2) \) and predicted value \( P[.] \). The prediction operation is applied on even poly-phase components \( I_e(z_1, z_2) \). In this case we simply consider the predictor as the average of two neighbouring even poly-phase samples.

\[
P[.] = \frac{1}{2} \left[ I_e(z_1, z_2) + I_e(z_1 + 1, z_2 + 1) \right]
\] (3.3)

Where \( I_e(z_1, z_2) \) and \( I_e(z_1 + 1, z_2 + 1) \) are two successive samples in z domain and \( I_e(n_1, n_2) \) and \( I_e(n_1 + 1, n_2 + 1) \) are corresponding inverses in spatial domain. The detailed coefficients are computed using the expression

\[
d(n_1, n_2) = I_o(n_1, n_2) - P[.]
\] (3.4)

The predication process produces details coefficients and the operation implies high pass filter.

Update operator \( U[.] \) updates the even poly-phase samples \( I_e(n_1, n_2) \) using the detailed coefficients computed \( d(n_1, n_2) \) in the prediction stage.
The update $U[.]$ is defined as a proportionality factor between the sum of approximate coefficients and mean of input matrix.

$$U[.] = \frac{1}{2} \left( \sum_{n_1, n_2} a(n_1, n_2) \right) \sum_{x, y} I(x, y)$$  \hspace{1cm} (3.5)

The update stage substitutes even samples $I_e(n_1, n_2)$ with

$$a(n_1, n_2) = I_e(n_1, n_2) + U[.]$$  \hspace{1cm} (3.6)

$a(n_1, n_2)$ are approximate coefficients representing low frequency components of the original image $I(x, y)$. The inverse process is quite opposite to that of the forward transformation as shown in figure 3.2.

Figure.3.2: Reconstruction LWT

### 3.3 Singular Value Decomposition

Singular Value Decomposition (SVD) [20] is a mathematical tool used in matrix diagonalization to compute singular value matrices from a host matrix. SVD is widely used in watermarking because of the advantage it offers in hiding the watermark effectively when changes occur in large singular values.
In watermarking SVD is used in combination with DWT [21]-[23] where watermark is embedded in the transform coefficients of the host image instead of pixels. A matrix in SVD is decomposed into three matrices. For a image matrix \( I(x, y) \in \mathbb{R} \) indicated as a real number \( \mathcal{J} \) of size \( m \times n \) with \( m \geq n \), the SVD is formulated as

\[
\mathcal{J} = U \Sigma V^T
\]  

(3.8)

Where \( U \) and \( V \) are orthogonal matrices of size \( m \times r \) and \( r \times n \) respectively. \( \Sigma \) is a diagonal matrix of size \( r \times r \) containing singular values of \( \mathcal{J} \). Here \( r \) is the rank of input matrix \( \mathcal{J} \).

\[
\Sigma = \begin{bmatrix}
\sigma_{11} & 0 & \ldots & 0 & 0 \\
0 & \sigma_{22} & \ldots & 0 & 0 \\
0 & 0 & \sigma_{33} & \ldots & 0 \\
\vdots & \ddots & \ddots & \ddots & \vdots \\
0 & 0 & \ldots & \sigma_{r_{1}r_{2}-1} & 0 \\
0 & 0 & \ldots & 0 & \sigma_{r_{1}r_{2}} \\
\end{bmatrix}
\]  

(3.9)

Where \( \sigma_i \)'s singular values of \( \mathcal{J} \) and their number is equal to rank of \( \mathcal{J} \). SVD offers distinct advantages such as efficiently representing indispensable algebraic properties of the image, where singular values \( \Sigma = \{\sigma_{11}, \sigma_{22}, \sigma_{33}, \ldots, \sigma_{r_{1}r_{2}-1}, \sigma_{r_{1}r_{2}}\} \) correspond to pixel brightness and image geometry features are modelled with singular vectors \( U \) and \( V \).

Moreover singular values are completely stable in the sense that a small commotion to the watermarked image will not appreciably modify the singular values, preserving the quality of the watermarked image and its contents for extraction.
3.4 Watermark Embedding Using LWT-SVD Algorithm

In this chapter, Lifting Wavelet Transform (LWT) and singular value decomposition are used together to accomplish the task of watermarking medical images with patients image. The watermarking embedding and extraction procedures are illustrated in figure 3.3 and figure 3.4 respectively.

This work is an attempt to insert patient’s image of size $64 \times 64$ into their medical images of size $256 \times 256$ instead of binary data of the patient as done by most of the researchers. This presents quite a challenging task to retain the medical information after watermarking and extraction of patient’s image at the doctor’s end even after attacks.

![Figure 3.3: Watermark Embedding Algorithm](image)
Medical Image Watermarking Process

Medical Images watermarking with their corresponding patient image is accomplished using the following steps.

**S1.** Carry out 1st level 2D Lifting Wavelet Transform (LWT) on the Medical Image (Cover Image) and decompose in to following sub-bands (LL, LH, HL, HH).

**S2.** Apply SVD to all sub-bands

\[ S^{(n)} = U^{(n)} \Sigma^{(n)} V^{(n)T} \]  \hspace{1cm} (3.10)

Where \( n \) is the sub-band pointer i.e. LL, LH, HL and HH.

**S3.** Modify the sub-bands singular values \( \Sigma^{(n)} \) by inserting the watermark i.e. patient image pixels directly using the expression

\[ WM^{(n)} = \Sigma^{(n)} + \alpha w^{(p)} \]  \hspace{1cm} (3.11)

\( w^{(p)} \) Corresponds to pixels values in the watermark. Here \( \alpha \) can take values in the range 0.007 to 0.07 and determines the strength of the watermark.

**S4.** Apply inverse singular value decomposition using the singular vectors \( U^{(n)} & V^{(n)T} \) from step 2. The latest modified sub-bands are produced using the formulation

\[ W^{(n)} = U^{(n)} WM^{(n)} V^{(n)T} \]  \hspace{1cm} (3.12)

Where \( W^{(n)} \) modified sub-bands.

**S5.** Finally, assemble all the modified sub-bands and apply inverse 2D Lifting Wavelet Transform (ILWT) which is formulated as

\[ W^{MT} = (W^{(n)})^{-1} \]  \hspace{1cm} (3.13)

\( W^{(n)} \) represents 4 sub-bands for n=1, LL, LH, HL, HH. \( W^{MT} \) is the watermarked medical image.
3.5 Watermark Patient Image Extraction Process

The watermarked medical image $w^m$ is sent remotely on the unsecured internet to a doctor. At the doctor’s end the system decouples the attacked watermarked medical image from the watermark for authentication that these medical images belong to that particular patient. The following steps are followed at the doctor’s side to extract the watermark patient image.

**S1.** The possibly attacked watermark medical image is treated with 2D Lifting wavelet transform (LWT) and decomposed to level 1 with 4 sub-bands LL, LH, HL and HH.

**S2.** Apply SVD to all sub-bands.

$$E_p^{(n)} = U_e^{(n)} \Sigma_e^{(n)} V_e^{(n)^T}$$  \hspace{1cm} (3.14)

**S3.** Apply inverse SVD but with orthogonal vectors derived from watermarking process.

$$E^{(n)} = U^{(n)} \Sigma_e^{(n)} V^{(n)^T}$$  \hspace{1cm} (3.15)

**S4.** Extract the watermark $E^{PI}$ patient image from the watermarked medical image using the following equation

$$E^{PI} = \frac{E^{(n)} - \Sigma_e^{(n)}}{\alpha}$$  \hspace{1cm} (3.16)

$E^{PI}$ is the extracted patient image watermark in level n.
3.6 Results and Discussion

This method is implemented on MATLAB 13.0.1 software with three different types of medical images which are considered as cover images. MRI, CT and Ultrasound medical images are used as cover images of standard resolution $256 \times 256$. Watermark is a patient image of resolution $64 \times 64$.

This method does not put a constraint on patient watermark image resolution which can be of the same size as the medical cover image. Since medical images are gray scale images, it is intended to consider grayscale patient image as watermark. The scaling factor $\alpha=0.07$ is used for watermarking in the experiments.
Other scaling factors that can be used are 0.05, 0.02 or two different scaling factors for approximate coefficients and detail coefficients.

The performance of the proposed medical image watermarking is judged by computing peak signal to noise ratio (psnr) and normalized cross correlation coefficient (ncc). These parameters will decide the robustness of the watermarking method using 2D LWT-SVD method.

Watermarking of medical images is quite sensitive process as the medical images contain information related to a disease of human subject. Corruption of the original medical image by watermarking process should be within the permissible limits of human perception. The visual sensitivity of the watermarked and extracted images is mathematically represented by calculating psnr and ncc.

**Embedded Peak Signal to Noise Ratio (psnr)**

Embedded psnr [25] is the measure of peak error between original image and watermarked image and is formulated as

\[
psnr = 10 \log_{10} \left( \frac{MN \max(\max(I^M(x,y))^2)}{\sum_{x \in N \ y \in M} (I^M(x,y) - W^M(x,y))^2} \right)
\]  

(3.17)

Where N and M represent image resolution. \(I^M(x,y)\) is the original medical image and \(W^M\) is the watermarked medical image. psnr is the peak signal to noise ratio in db which range between 40db to 60 db generally for good watermarking.
**Extracted Normalized Cross Correlation Coefficient (ncc)**

Normalized cross correlation is mostly used by pattern recognition research for measuring similarity between a query image and the images from the database. The cross correlation is normalized by subtracting the mean and dividing by standard deviation. Embedded normalized cross correlation coefficient gives the measure of closeness between watermarked image and original medical image.

\[
\text{ncc} = \frac{\sum_{x \in N} \sum_{y \in M} I^M(x, y) \times W^{Mq}(x, y)}{\sqrt{\sum_{x \in N} \sum_{y \in M} [I^M(x, y)]^2} \sqrt{\sum_{x \in N} \sum_{y \in M} [W^{Mq}(x, y)]^2}}
\]  

(3.18)

The values of normalized cross correlation coefficients (ncc) range from 0 to 1. Larger values of ncc are preferred for better watermarking.

Figure 3.5 shows brain MRI of a patient along with its lifting wavelet transform. LWT decomposes using debauches2 (db2) mother wavelet to a level-1 decomposition. MRI brain medical image(256×256) is used as cover image for watermarking in figure 3.6(a) and lena image is used as patient image(64×64) in figure 3.6(b).

LWT-SVD watermarking procedure as proposed embeds patient image into the watermarked brain MRI image as shown in figure 3.6(c). Figure 3.6(d) shows the extracted watermark of patient image. From figure 3.6 it can be observed that the watermarked image and extracted image match strongly enough as per human visual system.
Figure 3.5: Lifting Wavelet Using ‘db2’ (a) Brain MRI Image (b) its LWT

Figure 3.6: (a) MRI Cover Image (b) Patient Image Watermark (c) Watermarked MRI Image with Patient Image using LWT-SVD (d) Extracted Watermark
This shows the robustness of LWT-SVD algorithm. Similar results can be obtained using Computer Tomography (CT) and Ultrasound (US) Medical images as cover images. The results for CT and US are shown in figures 3.7, 3.8, 3.9 and 3.10 respectively.

**Figure.3.7:** Lifting Wavelet using ‘db4’ Mother wavelet (a) CT Medical Cover Image (b) its LWT

**Figure.3.8:** (a) CT Cover Image (b) Patient Image Watermark (c) Watermarked CT Image With Patient Image using LWT-SVD (d) Extracted Watermark
Figure 3.9: Lifting Wavelet using 'db6' Mother wavelet (a) US Medical Cover Image (b) its LWT

Figure 3.10: (a) US Cover Image (b) Patient Image Watermark (c) Watermarked CT Image With Patient Image using LWT-SVD (d) Extracted Watermark
The CT and US medical cover images are watermarked using mother wavelets ‘db4’ and ‘db6’ lifting scheme. Visually comparing the watermarked medical images from figures 6, 8 and 10(c) with patient image reveal that there is remarkably no deviation in case of MRI and CT for ‘db2’ and ‘db4’ wavelets except for a small one in case of US medical image from its watermark US image for ‘db6’ mother wavelet.

Results are also formulated using equations 3.17 and 3.18 in Table-VI for the embedded watermark and original medical image for all three different medical images. The data interpretation highlights the effectiveness of the LWT-SVD watermarking procedure for medical image watermarking with patient image as payload.

Table-VI: PSNR and NCC Embedded watermark

<table>
<thead>
<tr>
<th>Cover Medical Image</th>
<th>PSNR(db)</th>
<th>NCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRI</td>
<td>46.8998</td>
<td>0.9869</td>
</tr>
<tr>
<td>CT</td>
<td>47.3565</td>
<td>0.9899</td>
</tr>
<tr>
<td>Ultrasound(US)</td>
<td>45.3454</td>
<td>0.9768</td>
</tr>
</tbody>
</table>

From Table-VI psnr in db for MRI, CT and US watermarks are 46.8998db, 47.3565db and 45.3454db respectively. Comparing with psnr values of dwt-svd watermarking in [22] our proposed lwt-svd on medical images are almost within the prescribed values of watermarking [22].

Normalized Cross Correlation (ncc) coefficient is good for MRI and CT with 0.9869 and 0.9899 compared to US at 0.9768. Again the values are within the permissible range as proposed by lwt-svd watermarking and compared to results in [22]. From figures 3.6(c), 3.8(c) and 3.10(c) it can be visually confirmed that the lwt-svd produces high quality medical watermarked images which preserve medical information and are similar to that of original medical images.
The extracted watermark images are shown in figures 3.6(d), 3.8(d) and 3.10(d) which are extracted from MRI, CT and US images using ‘db2’, ‘bd4’ and ‘db6’ mother wavelets. The extracted watermark from MRI watermarked image using ‘db2’ is of high quality compared to watermark extracts from CT and US using ‘db4’ and ‘db6’.

The watermarked medical images are transmitted on unsecured networks making them prone to attacks from various unlawful elements present on the network. Hence to simulate attack environment on the internet for our research we modeled six types of commonly used attacks with different values making the total number of attacks to fifteen.

We then compute normalized cross correlation coefficient form equation 3.18 for the extracted watermarked images. The values are put up in Table-VII. Generally the ncc coefficient for better watermark is something above 0.75[22].

For remarkably excellent correlation the value of ncc should be around 0.9999 or 1. A value of zero for ncc indicates a complete un-correlation between the original cover image and the watermarked image. Table-VII ncc values are computed in all wavelet sub bands (LL, LH, HL, HH) of watermarked image.

The watermarked medical image is subjected to six attack categories such as a 3×3 window mean filtering, a 3×3 window median filtering, 10°, 20°, 30° and 40° rotation, salt & pepper noise of noise densities 0.01, 0.1, 0.3 and 0.5, shear with x=0.5, y=0.5 and x=0, y=1, and finally crop with crop area [5, 5], [50, 50] and [100, 100]. Table-VII shows the robustness of lwt-svd under these attacks.
### Table VII: NCC for extracted watermarked images

<table>
<thead>
<tr>
<th>Attacks</th>
<th>Magnetic Resonance Imaging(MRI)</th>
<th>Computer Tomography(CT)</th>
<th>Ultrasound (US)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>'bd2'</td>
<td>'bd4'</td>
<td>'db6'</td>
</tr>
<tr>
<td><strong>Mean Filtering (3×3)</strong></td>
<td>LL 0.9899 LH 0.9789 HL 0.9765 HH 0.9799</td>
<td>LL 0.9865 LH 0.9854 HL 0.9843 HH 0.9811</td>
<td>LL 0.9754 LH 0.9786 HL 0.9765 HH 0.9654</td>
</tr>
<tr>
<td><strong>Median Filtering (3×3)</strong></td>
<td>0.8026 LL 0.7916 LH 0.7892 HL 0.7926 HH 0.7992</td>
<td>0.7926 LL 0.7981 LH 0.797 HH 0.7938</td>
<td>0.7881 LL 0.7913 LH 0.7892 HH 0.7781</td>
</tr>
<tr>
<td><strong>Rotation (10°)</strong></td>
<td>0.9776 LL 0.9666 LH 0.9642 HL 0.9676 HH 0.9742</td>
<td>0.9731 LL 0.972 HH 0.9688</td>
<td>0.9631 LH 0.9663 HH 0.9642 HH 0.9531</td>
</tr>
<tr>
<td><strong>Rotation (20°)</strong></td>
<td>0.9653 LL 0.9543 LH 0.9519 HL 0.9553 HH 0.9619</td>
<td>0.9608 LL 0.9597 HH 0.9565</td>
<td>0.9508 LH 0.954 HH 0.9519 HH 0.9408</td>
</tr>
<tr>
<td><strong>Rotation (30°)</strong></td>
<td>0.953 LL 0.942 LH 0.936 HH 0.9366</td>
<td>0.9496 HH 0.9474</td>
<td>0.9442 LH 0.9385 HH 0.9417 LL 0.9396 HH 0.9285</td>
</tr>
<tr>
<td><strong>Rotation (40°)</strong></td>
<td>0.9407 LL 0.9297 LH 0.9273 HL 0.9307 HH 0.9373</td>
<td>0.9362 LL 0.935 HH 0.9319</td>
<td>0.9262 LH 0.9294 HH 0.9273 HH 0.9162</td>
</tr>
<tr>
<td><strong>Salt &amp; Pepper Noise</strong></td>
<td>0.7007 LL 0.6897 LH 0.6873 HL 0.6907 HH 0.6973</td>
<td>0.6962 LL 0.6951 HH 0.6919</td>
<td>0.6862 LH 0.6894 HH 0.6873 HH 0.6762</td>
</tr>
<tr>
<td>(density=0.01)</td>
<td>0.6884 LL 0.6774 LH 0.675 HH 0.6784</td>
<td>0.685 LL 0.6839 HH 0.6828</td>
<td>0.6796 LH 0.6739 HH 0.6771 LL 0.675 HH 0.6639</td>
</tr>
<tr>
<td><strong>Salt &amp; Pepper Noise</strong></td>
<td>0.6761 LL 0.6651 LH 0.6627 HL 0.6661 HH 0.6727</td>
<td>0.6716 LL 0.6705 HH 0.6673</td>
<td>0.6616 LH 0.6648 HH 0.6627 HH 0.6516</td>
</tr>
<tr>
<td>(density=0.1)</td>
<td>0.6638 LL 0.6528 LH 0.6504 HL 0.6538 HH 0.6604</td>
<td>0.6593 LL 0.6582 HH 0.655</td>
<td>0.6493 LH 0.6525 HH 0.6504 HH 0.6393</td>
</tr>
<tr>
<td><strong>Salt &amp; Pepper Noise</strong></td>
<td>0.9456 LL 0.9346 LH 0.9322 HL 0.9356 HH 0.9422</td>
<td>0.9411 LL 0.94 HH 0.9368</td>
<td>0.9311 LH 0.9343 HH 0.9322 HH 0.9211</td>
</tr>
<tr>
<td>(density=0.5)</td>
<td>0.9443 LL 0.9333 LH 0.9309 HL 0.9343 HH 0.9409</td>
<td>0.9398 LL 0.937 HH 0.9355</td>
<td>0.9298 LH 0.933 HH 0.9309 HH 0.9198</td>
</tr>
<tr>
<td><strong>Shear (x=0.5, y=0.5)</strong></td>
<td>0.9913 LL 0.9834 LH 0.9776 HL 0.981 HH 0.9876</td>
<td>0.9865 LL 0.9854 HH 0.9822</td>
<td>0.9765 LH 0.9797 HH 0.9776 HH 0.9665</td>
</tr>
<tr>
<td><strong>Shear (x=0.2, y=0)</strong></td>
<td>0.9784 LL 0.9674 LH 0.965 HH 0.9684 HH 0.975</td>
<td>0.9739 LL 0.9728 HH 0.9696</td>
<td>0.9639 LH 0.9671 HH 0.965 HH 0.9539</td>
</tr>
<tr>
<td><strong>Crop(5,5)</strong></td>
<td>0.9677 LL 0.9567 LH 0.9543 HL 0.9577 HH 0.9643</td>
<td>0.9632 LL 0.9621 HH 0.9589</td>
<td>0.9532 LH 0.9564 HH 0.9543 HH 0.9432</td>
</tr>
<tr>
<td><strong>Crop(50,50)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Crop(100,100)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Six different types of attacks on the watermarked MRI image is shown in figure 3.11. Figure 3.11(a) gives 3×3 window mean attack, 3.11(b) median attack, figure 3.11(c) rotation attack, figure 3.11(d) noise attack, figure 3.11(e) shear attack and figure 3.11(f) shows crop attack on watermarked MRI image with patient data of size 64×64.

The extracted watermark after attacks is shown in figure 3.12. Figure 3.13 shows attacks on watermarked CT images and figure 3.14 shows the extracted watermarks after attacks. Finally the US watermarked images are attacked and watermark extracted are shown in figure 3.15 and 3.16 respectively.
Figure 3.11: MRI Watermarked Images with 'db2' after (a) 3×3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks.

Figure 3.12: Extracted Patient images from MRI Watermarked Images with 'db2' after (a) 3×3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks.
**Figure 3.13:** CT Watermarked Images with ‘db4’ after (a) 3x3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks.

**Figure 3.14:** Extracted Patient images from CT Watermarked Images with ‘db4’ after (a) 3x3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks.
Figure 3.15: Ultrasound (US) Watermarked Images with ‘db6’ after (a) 3×3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks.

Figure 3.16: Extracted Patient images from US Watermarked Images with ‘db6’ after (a) 3×3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks.
Comparing the figures 3.11 to figure 3.16 visually and computed ncc values in table-I of three types of medical cover image for ‘db2’, ‘db4’ and ‘db6’ wavelets the following conclusions can be drawn. One prominent conclusion is that the medical watermarked images get affected by noise in a remarkable manner compared to other attacks.

This can be understood by observing the values from table-II where ncc for salt & pepper noise for all densities produced very poor results. Visually also 3.11(d), 3.13(d) and 3.15(d) the watermarked medical image is completely lost except for the edges. At the same time the extracted watermark from the noise attacked watermarked image is in good condition visually and the ncc is around 0.8223.

Except noise attack, remaining attacks does not affect the proposed LWT-SVD watermarking and extraction processes. From the figures 3.14, 3.16 and 3.18 it can be visually noted that ‘db2’ lifting wavelet scheme provides good quality extractions compared to ‘db4’ and ‘db6’ lifting schemes.

Figure 3.17 plots the ncc values against attacks for MRI with ‘db2’, CT with ‘db4’ and US with ‘db6’ extracted patient images. The attacks are labeled on x-axis instead of full naming. The graph shows db2 and db4 mother wavelets perform well for lwt-svd watermarking procedures compared to db6.

Comparing dwt-svd watermarking procedure with lwt-svd technique for medical images using normalized cross correlation coefficient values, we found lwt-svd performs better than the dwt-svd. The plot in figure 3.18 proves the above statement. The reason behind dwt’s loss to lwt’s lies in the inverse transformation which is an approximation process in case of dwt.
**Figure 3.17:** ncc of extracted patient images from MRI, CT and US Watermarked Images against attacks

**Figure 3.18:** ncc of extracted patient images from MRI, CT and US Watermarked Images against attacks in case of dwt-svd and lwt-svd
The inverse process in lwt is renunciation of the processes performed during the forward transformation which retains sensitive information in case of medical image watermarking. The rectangular marking show where dwt-svd failed to make an impression on medical image watermarking against attacks.

Further the LWT-SVD based medical image watermarking process with ‘db2’ is tested by increasing the resolution of patient image to 256×256 which is equal to the resolution of the medical cover image. The patient images also include on top of the image their personal information regarding name, age, previous medical history. Figure 3.19 shows the watermarked MRI and extracted patient image both of same resolution. Figure 3.20 and 3.21 show watermarked images and extracted images after attacks.

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**Figure.3.19:** MRI Watermarked Images with ‘db2’ after (a) 256×256 cover image (b) 256×256 patient image as watermark,(c) 256×256 watermarked image,(d) 256×256 Extracted watermark
**Figure 3.20:** MRI Watermarked Images with ‘db2’ after (a) 3×3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks

**Figure 3.21:** Extracted 256×256 Patient images from MRI Watermarked Images with ‘db6’ after (a) 3×3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks
Similar procedure is repeated using CT images for a 256×256 patient image watermark with the proposed lwt-svd watermarking procedure. Figures 3.22 show the watermarked CT image and extracted patient image. Figures 3.23 and 3.24 show the attacks on the watermarked CT images and extraction of watermark patient images after attacks respectively.

**Figure 3.22:** CT Watermarked Images with ‘db2’ after (a) 256×256 cover image (b) 256×256 patient image as watermark, (c) 256×256 watermarked image, (d) 256×256 Extracted watermark
Figure 3.23: CT Watermarked Images with ‘db2’ after (a) 3x3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks.

Figure 3.24: Extracted 256x256 Patient images from CT Watermarked Images with ‘db6’ after (a) 3x3 window mean attack, (b) median attack, (c) rotation attack, (d) noise attack, (e) shear attack and (f) shows crop attacks.
3.7 Conclusion

In this chapter lifting scheme of wavelet transform and singular value decomposition (LWT-SVD) is proposed for watermarking different types of medical images such as MRI, CT and US with patient image as watermarks. In this method the singular values of the cover image are modified to create a watermarked medical image.

Experimental results demonstrate that the lifting wavelet transform is a better prospect for medical image watermarking scheme compared to normal discrete wavelet transform. The results prove this fact visually and mathematically by computing psnr and ncc values.

Experiments are also performed by simulating the attacks which prove the robustness of the LWT-SVD method for medical image watermarking towards attacks. The proposed method does not put constraints on the resolution of the watermarks used.

The only short coming in this watermarking algorithm is the loss of information in watermarked medical image under noise attacks. The extracted watermark in such situations can easily be detected by the hackers. Hence encrypted watermark patient image is used for watermarking.

The next chapter a more practically implementable medical image watermarking algorithm is based on RSA encryption in wavelet domain. Patient image watermark is encrypted and is used for watermarking medical images from various sources.