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Linear Discriminate Analysis based Robust Watermarking in DWT and LWT Domain with PCA based Statistical Feature Reduction

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Abstract: With aiming to design a novel image watermarking technique, this paper presents a novel method of image watermarking using lifting wavelet transform, discrete wavelet transform, and one-dimensional linear discriminate analysis. In this blind watermarking technique, statistical features of the watermarked image have been incorporated for preparing the training set and testing set. After that, the principal component analysis is applied to reduce the obtained feature set, so the training time is reduced to the desired level and accuracy is enhanced. The one-dimensional linear discriminate analysis is used for binary classification as it has the ability to classify with good accuracy. This technique applies discrete wavelet transform and lifting wavelet transform in two different watermarking schemes for the image transformation. Both transformations give higher tolerance against image distortion than other conventional transformation methods. One of the significant challenges of a watermarking technique is maintaining the proper balance between robustness and imperceptibility. The proposed blind watermarking technique exhibits the imperceptibility of 43.70 dB for Lena image in case of no attack for the first scheme (using LWT) and 44.71 dB for the second scheme (using DWT+LWT). The first watermarking scheme is tested for robustness, and it is seen that the given scheme is performing well against most of the image attacks in terms of robustness. This technique is compared using some existing similar watermarking methods, and it is found to be robust against most image attacks. It also maintains the excellent quality of the watermarked image.

Index Terms: Lifting wavelet transform **(**LWT), Discrete wavelet transform (DWT), Principal component analysis (PCA), One-dimensional linear discriminate analysis (1D-LDA), Statistical feature, robust watermarking, blind watermarking

1. Introduction

With the advancement in technology, digital data is enormously growing in various dimensions. The extensive usage of digital data has now raised the challenge of protecting the integrity and security of data over the internet. With the advancement in technology, altering or updating digital data has become exceedingly more accessible and more straightforward. In order to provide copyright protection and protect the integrity of digital data, there is a requirement of methods or techniques that can assure the integrity of digital data in a sophisticated manner. Various techniques have been suggested for copyright protection and preventing illegal data modification in the literature. Digital image watermarking is one of the oldest and most trusted ways of protecting digital data in a simplified manner [1]. Some other techniques are also mentioned in the literature to protect digital content's integrity, like Steganography and cryptography. However, Steganography suffers from the problem of significant overhead to hiding a very tiny amount of information [2]. Cryptography is lacking because once a secret message is decoded, it can be copied illegally any number of times without any overhead [1]. Keeping the above things in mind, the image watermarking technique has become one of the possible solutions for securing the integrity of digital content.

One of the significant challenges for a watermarking system is to maintain an adequate balance (trade-off) between the image qualities, capacity, and security of the watermarked image [3]. The basic requirements for a watermarking system are capacity, robustness, security, and imperceptibility. Capacity is the number of bits embedded using the watermarking process; robustness means exhibiting good performance against most image attacks, and imperceptibility means satisfying watermarked images. Robustness is measured and calculated using normalized coefficient (NC) and bit error rate (BER). On the other hand, imperceptibility is also a standard measure and is calculated in terms of the peak signal to noise ratio (PSNR). On the basis of robustness, a watermarking system can be categorized as robust watermarking, fragile watermarking, and semi-fragile watermarking [3]. This technique presents a robust and blind watermarking technique. The embedding and extraction of a watermark can be done using the spatial and frequency transformation of the image. After reviewing various pieces of literature, it has been seen that spatial domain-based watermarking is mainly used for tamper detection and image authentication [4].

In contrast, the transformation domain-based watermarking is extensively used for copyright protection as it is more robust than other spatial domain based watermarking. A cover image can be transformed using discrete cosine transform (DCT) [5-6], discrete fourier transform (DFT) [7-8], discrete wavelet transform (DWT) [9-12], redundant discrete wavelet transforms (RDWT) [13-14], and lifting wavelet transform (LWT) [15-19] and each of the transformation has its own merits, and demerits like LWT has the merit of sustaining higher tolerance against distortion of watermarked image because of its higher energy compaction properties than any other decomposition method. Singular value decomposition (SVD) [10, 12, 14] is also used by some researchers for strengthening the watermark against various image attacks because of its good energy compaction property.

A cover image can be partitioned into different sub-bands and each sub-band has its own merits and demerits. Different sub-bands of the cover image has been utilized for embedding purpose like HL is selected by Khare, P. & Srivastava, V. K. [9], LH sub-bands is used by Verma, V. S. et al. [17], a combination of LL and LH has been used by Talbi, M. et al. [19]. A study using different sub-band has been done by Islam, M et al. [18], in which nine sub-bands out of sixty-four sub-bands have been chosen for embedding and analyzed the effect of image attacks on the watermarked image on each sub-band using SVM and it is concluded that sub-band 7 shows good results in terms of both robustness measure and imperceptibility measure. The embedding in sub-band 7 also provides a good imperceptibility (PSNR) of 44.0719 dB, and embedding in LL, LH, or HL sub-band shows an average PSNR of 44dB, which is quite good as the quality of an image is concerned. This method provides good robustness against all attacks except some noising and de-noising attacks.

A robust image watermarking scheme for medical images has been proposed by Anand, A. and Singh A. K. [12] using DWT and SVD. To improve the security of the proposed system multiple watermark has been applied and before embedding the watermark hamming code is applied to the text watermark for reducing the noise. DWT has been selected for the decomposition because of spatial frequency property of DWT, which helps to recognize the area where the embedding can be done with high imperceptibility. In the proposed scheme the Chaotic-LZW shows the good performance over other scheme. A blind image watermarking using LWT and SVM has been proposed by Verma et al. [17] in which watermarking is performed on twelve standard images and PCA is used for reducing the number of features. Here watermark extraction is treated as a binary classification and SVM is applied for the binary classification. Twelve statistical feature of watermarked image is extracted and passed to the PCA for feature reduction. LWT is used for the decomposition because of its energy compaction properties and generalization capability of SVM makes this scheme more robust than the other scheme. SVM with RBF kernel shows the good performance over other methods. Though this method needs further improvement in case of rotation and translation attacks.

A deep-learning based multiple images watermarking scheme has been given by Mahto, D. K. et al. [20]. The spatial and transforms domain-based approach is the foundation for this concept. The watermarked image is encrypted using an improved encryption algorithm, and the suggested system's robustness is increased further by using a de-noising convolution neural network. For the experiment, 14 standard color images are selected. And average PSNR and average NC are both 57.7124 and 1, respectively. LWT-DCT-SVD based non-blind dual watermarking is given by Zear, A. et al. [21] for color images. In this scheme, a text watermark with a size of 64x64 pixels is embedded into a color cover image with a size of 512x512 pixels employing the LH3 sub-band and secured using the message digest hash function. The obtained results are also compared using the RGB, YIQ and YCbCr color models using the different scaling factor, different size of text watermark for different image attacks. The greatest PSNR obtained is 34.60 dB at scaling factor 0.01 for the Y part of the YIQ model.

The literature has noticed that the use of machine learning [15, 17-19, 22-23] and deep learning [24-25] methods for image watermarking has increased drastically due to their excellent performance over other conventional methods. Deep learning requires excellent computational power in terms of processing speed and memory; therefore, it is always not possible to use deep learning until and unless it is most needed, whereas machine learning requires less computation. Various machine learning-based watermarking has been proposed by researchers like support vector machine (SVM) based, k nearest neighbour (KNN) based and artificial neural network (ANN) based watermarking is explored [18], and it has been found that SVM with RBF kernel gives good results as compared to ANN and KNN. Another study based on SVM has been done by [17]. The support vector machine using RBF kernel and PCA gives good results, balancing the robustness and imperceptibility for most image attacks except the rotation and translation attacks.

Linear discriminate analysis (LDA) is also a supervised machine learning (ML) algorithm. In the literature, there are two types of LDA elaborated, i.e. dimensional LDA (1D-LDA) and two dimensional LDA (2D-LDA). Some literature has given sufficient knowledge of these two types of LDA. Zheng, W.S. et al. [26] have given a literate in which both types of LDA have been compared conceptually and experimentally, and it is found that both of the LDA are better in terms of their usages and the domain where it is applied. Zheng, W.S. et al. [26] have presented a comprehensive comparison between 1D-LDA and 2D-LDA. It is found that 2D-LDA can perform better when the training samples are less and the features used to discriminate are small; otherwise, the 1D-LDA performs well. The 2D-LDA loses some covariance information while convergence from 1D-LDA to 2D-LDA so; therefore, the conventional 1D-LDA is employed in the proposed method.

The watermark bit extraction from the watermarked image is solved using the classification of binary bits 0 or 1 in the given literature [17, 18], in which the SVM is used. The model is trained using the reference watermark (randomly generated) of size 512 and tested using the signature watermark of size 512 (watermark image) by applying the SVM using the RBF kernel to solve the watermarking extraction using the binary classification problem. LDA is applied for the color image watermarking in various works of literature like Fu, Y.G. et al. [27] and Chang, T. J. et al. [28] have applied LDA instead of SVM and other machine learning methods. LDA has good learning ability in a supervised learning environment where the response is given based on the relationship between input and output; it can learn more quickly and efficiently compared to the other machine learning method. One of the possible reasons for applying LDA is that it can learn the relation between the watermarked position and its neighbour in an efficient way compared to other ML models [27]. It is worthy to note that Fu, Y.G. et al. [27] and Chang, T. J. et al. [28], have applied the LDA for color images, so it would be interesting to apply LDA for the grayscale images, however data hiding in color image require some addition consideration because of various red, green and blue color bands, but in case of grayscale images, it is easier to apply it for watermarking. In the recent work, many methods of watermarking have been reported, which have incorporated PCA [17] and 2D-LDA (two dimensional LDA) [27, 28] for the extraction of watermark bits and apart from the watermarking, these two techniques have been successfully applied for the other application such as pattern recognition, classification, medical security, function estimation, etc. Many other observations in the past literature show that LDA and PCA's performance is better compared to other traditional ML models. The reason behind being so effective is the ability to map the relationship between the pixels with the help of various algebraic transforms and matrix decomposition. Whenever LDA is used for the image, it must transform the image matrices to an equal vector space to reduce the complexity. Based on the above observation, here 1D-LDA and PCA have been selected for solving the problem of watermark extraction.

This research paper presents a robust watermarking scheme for grayscale images, which incorporates the 1D-LDA and PCA. In the given technique, two watermarking scheme is presented, for the first scheme, LWT is applied up to the third level of decomposition, and in the second scheme, first DWT is applied up to the second level. Then third level LWT is performed for obtaining 32*32 blocks, each having 2*2 sizes. Twelve statistical features are extracted from the given block, which are feed to the PCA for feature reduction so in this way total six features is finally selected after the feature reduction. Now six reduced features and the coefficient value of 512 blocks are combined to get the training set of size 512*10, which is used for the 1D-LDA training purpose. Here 512 bits are utilized for training purpose, and 512 bits is utilized for testing purpose.

This paper is organized as follows. Section 1 deal with the introduction, section 2 contains the basic concept of the study. The proposed watermarking methodology is mentioned in section 3. The result and discussion are mentioned in section 4, and section 5 shows the paper's conclusion.

2. Preliminary

A. One dimensional linear discriminate analysis (1D-LDA)

1D-LDA is a form of LDA in which all the operations are performed using the vectors rather than matrix as done in 2D-LDA. LDA is a linear machine learning model, which was first proposed by Fisher in the year 1936 for the binary classification, but later it was extended for the multiclass classification in the year 1948 by C. R. Rao. The LDA works with the principle of maximizing the variance between the means of two classes and minimizing the variance within each class. LDA project data from an S dimension feature down to an S' dimension space for solving the classification problem such that $S > S'$ [26].

Let $\left\{\left(x_1^1, X_1^1, C_1\right),\ldots,\left(x_{N1}^1, X_{N1}^1, C_1\right),\ldots,\left(x_1^L, X_1^L, C_1\right),\ldots,\left(x_{NL}^L, X_{NL}^L, C_1\right)\right\}$ be image sample of L belongs to different classes. The m-dimensional vector $x_i^K \in R^m$ is the i^{th} sample of the j^{th} class C_k and $x_i^K \in R^{row\,x\,col}$ is its corresponding $rowXcol$ image matrix, where $i = 1, 2, \ldots\ldots N_k$ where N_k is number of training samples belongs to class C_k µ

1D-LDA aiming at finding the discriminative vector $\mathrm{S}_{\mathrm{opt}}$ in such a way that

$$\mathrm{S}_{\mathrm{opt}} = \operatorname{argmax} \frac{S^T D_b S}{S^T D_w S'} \tag{1}$$

Where

$$D_b = \sum_{K=1}^{L} \frac{Nk}{N} (u_K - u)(u_k - u)^T,\ D_w = \frac{1}{N} \sum_{K=1}^{L} \sum_{i=1}^{Nk} \left(X_i^k - u_k \right)\left(X_i^k - u_k \right)^T = \sum_{k=1}^{L} \frac{Nk}{N} S_w^k,\ S_w^k = \frac{1}{Nk} \sum_{i=1}^{Nk} \left(X_i^k - u_k \right)\left(X_i^k - u_k \right)^T$$

represents between-class matrix, within-class scatter matrix and within-class scatter matrix of class C_k. Here N shows the total number of samples, and u_k is corresponding mean vector of the sample class C_k and u is defined as the mean vector of all sample classes.

$$u_k = \frac{1}{N_k} \sum_{i=1}^{N_k} X_i^k \tag{2}$$

$$u = \sum_{k=1}^{L} \frac{N_k}{N} u_k \tag{3}$$

B. Principal component analysis (PCA)

PCA works based on unsupervised machine learning technique and it is used to reduce the number of features. In PCA dimension of input data is reduced after analyzing the most prominent features and it eliminates the features which are not important. Let us consider a data set $xd = (\mathrm{x1}, \mathrm{x2}, \ldots\ldots \mathrm{xn})^T$ having n-dimension, then using PCA, aims at finding its lower dimension corresponding representation, $yd = (\mathrm{y1}, \mathrm{y2}, \ldots\ldots \mathrm{yk})^T$ with $k \le n$, that contains all the data using some method. PCA is known as karhunen-loeve transform (KLT), Singular value decomposition (SVD) and empirical orthogonal function (EOF) method [29, 30].

C. Lifting wavelet transform (LWT)

Lifting wavelet transform (LWT) or Integer wavelet transform (IWT) has been proposed by Sweldens in the year 1966 [31]. The LWT based watermarking is popularized because of its more energy compaction property. In LWT transform, an image is decomposed into the integer domain rather than the floating point domain because of lifting step. LWT based watermarking takes less memory and time because of treating problem in the integer domain rather than floating point domain. LWT is composed of three steps, i.e. splitting, predict, update. LWT based watermarking is gaining attention because of its various advantage over other watermarking scheme based on other wavelet methods.

3. Proposed Method

This section of the paper presents the watermarking scheme in the LWT and DWT domain using 1D-LDA and PCA based statistical feature reduction. As we all know, the image pixels are naturally correlated with each other, and these relations can be further utilized to learn the LDA machine learning model. It has been seen that whenever a watermarked image is attacked intentionally or unintentionally, its relation of pixels remains unchanged or a tiny changes and this advantage can be utilized for designing robust digital image watermarking scheme. Here, *for LWT based watermarking scheme*, a cover image is decomposed into 3rd level using LWT and LH3 sub-band is chosen for the embedding purpose and size of LH3 sub-band is 1024 block of size 2*2 matrix. *For DWT+LWT based watermarking scheme* get the 2nd level DWT transform of cover image and then get the next one level to transform using LWT and select the LH3 sub-band of block size 1024. Out of these 1024 blocks, 512 blocks are used for training purposes, and 512 blocks are used for testing purposes. This watermarking scheme uses two types of watermarks, namely reference watermark and signature watermark. Reference watermark is generated randomly watermark used for LDA training purposes, whereas the signature watermark is the original watermark used for LDA testing purposes. Both the signature and reference watermark are of size 512 bits, and these two are concatenated for getting the watermark bit of length 1024 bits used for the embedding purpose. For watermark extraction, the statistical features such as Kurtosis (f1), Skewness (f2), Entropy (f3), Standard deviation (f4), Mean (f5), Variance (f6), Mode (f7), Median (f8), Covariance (f9), Poisson probability distribution (f10), Moment (f11), and Quartiles (f12) value of all the corresponding blocks are calculated to form a feature set of size 512*12 and then these feature set (f1, f2, ……………, f12) is given to the PCA for reducing the feature set. The size of the reduced feature set is 512*6. Now this reduced feature set is combined along with the coefficient of LWT (for the first scheme) or DWT+LWT (for the second scheme) 3rd level LH3 sub-band having size 2*2, so in this way total 512*10 feature is used for the supervised training purpose and the size of the target variable is 512*1. The testing feature set is prepared the same way as a training feature set. Once the embedding is done, the training set is used for the LDA training purpose, and the testing set is used for the testing purpose. Once the LDA is trained, the trained LDA model is utilized for the binary classification in order to get the watermark from the watermarked image.

A. Watermark embedding process

In this scheme watermark having length, l_w is partitioned into two parts, i.e. the reference part (R_r) of length l_r and the signature part (S_r) of length l_s. Here the reference part is randomly generated and shuffled using secret seed key K3. Both the signature and reference parts have been concatenated to form a single watermark and represented as $W = R_r + S_r = w1 + w2 +, \ldots\ldots\ldots, +w_{l_r} + w_{l_{r+1}} +, \ldots\ldots, +w_{l_{r+}l_s}$. Here the reference part is utilized to generated training set and signature (original) watermark are used to generate the testing set.

The mathematical equation to add the watermark bit 1 and 0 is as follows:

If watermark bit = 1,

$x(n)_i = x(n)_i + T$, if $\mathrm{Diff}_i^{\max} < \max(\sigma, T)$,

$$\text{Else } x(n)_i = x(n)_i \tag{4}$$

And, if the watermark bit=0

$$x(n)_i = x(n)_i - \mathrm{Diff}_i^{\max} \tag{5}$$

Where T represents threshold, and $\mathrm{Diff}_i^{\max}$ shows the variation among the two largest values of the respective i^{th} block. The averaging difference of coefficient value σ for all N_w blocks is shown as:

$$\sigma = \frac{\sum_{i=1}^{Nw} \mathrm{Diff}_i^{\max}}{Nw} \tag{6}$$

Here N_W represents the sum of the number of blocks in LH3 sub-band where the watermark bits are added.

The steps for watermark embedding process are listed below:

Step 1: For the first scheme, i.e. LWT based, obtain the 3rd level LH3 sub-band of size (64*64) of the cover image (512*512) using LWT transform. OR

For second scheme i.e. DWT+LWT based, obtain the 2nd level DWT sub-band of cover image then obtain the next one level of LWT transform.

Step 2: Shuffle coefficients of LH3 sub-bands using secret seed key K1.

Step 3: Form a block of size (2*2) using non-overlapped coefficients of LH3 sub-bands.

Step 4: Shuffle obtained 1024 blocks utilizing secret seed key K2.

Step 5: Compute the average coefficient difference σ using eq. (6)

Step 6: Concatenate the signature (original) watermark and reference watermark to form a 1-D array of the binary watermark (W) of length N_w and shuffle the bits using seed key K3.

Step 7: For all N_w bits of binary watermark, do the following

7.1. Calculate the two largest coefficients from each block say $cf(n)$ and $cf(n-1)$.

7.2. If the watermark bit is 1, then modify $cf(n)$ using eq. (4)

7.3. If the watermark bit is 0, then modify $cf(n)$ using eq. (5)

Step 8: Inversely shuffle all the updated blocks and coefficient utilizing the same seed key as used in the step 4 and 2.

Step 9: Apply inverse LWT or inverse DWT+LWT transform to get the watermarked image.

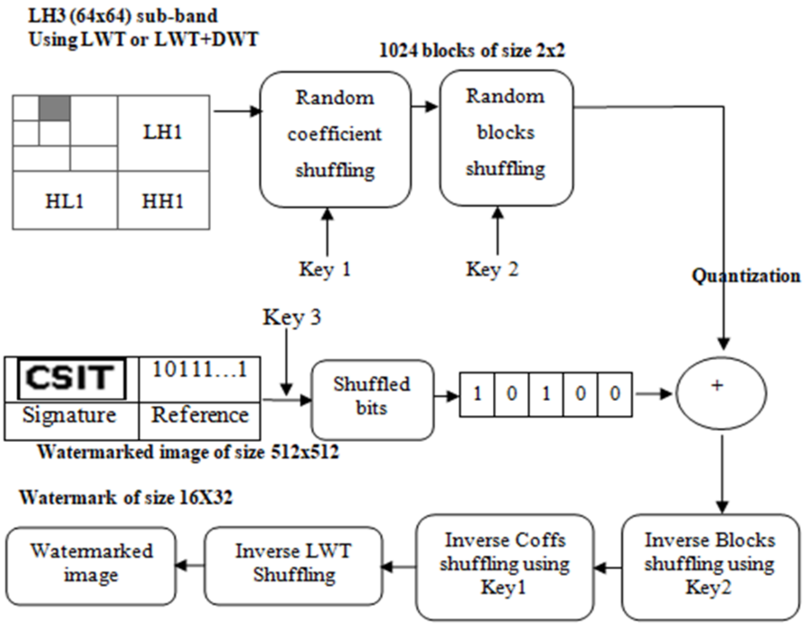

Fig. 1. Watermark embedding procedure

B. Watermark extraction process

In the proposed research, the watermark extraction problem is treated as the binary classification problem where LDA is applied to extract the binary watermark, which involves two class labels, "0" and class "1". It is very clear from the literature that LDA has a potent learning capacity as it can learn from the relation of the correlation of the pixel present in the image. Also, it is observed that whenever an image is attacked, the relationship between pixels remains unchanged, or a tiny change is done, so this advantage can be used to make LDA learn more efficiently.

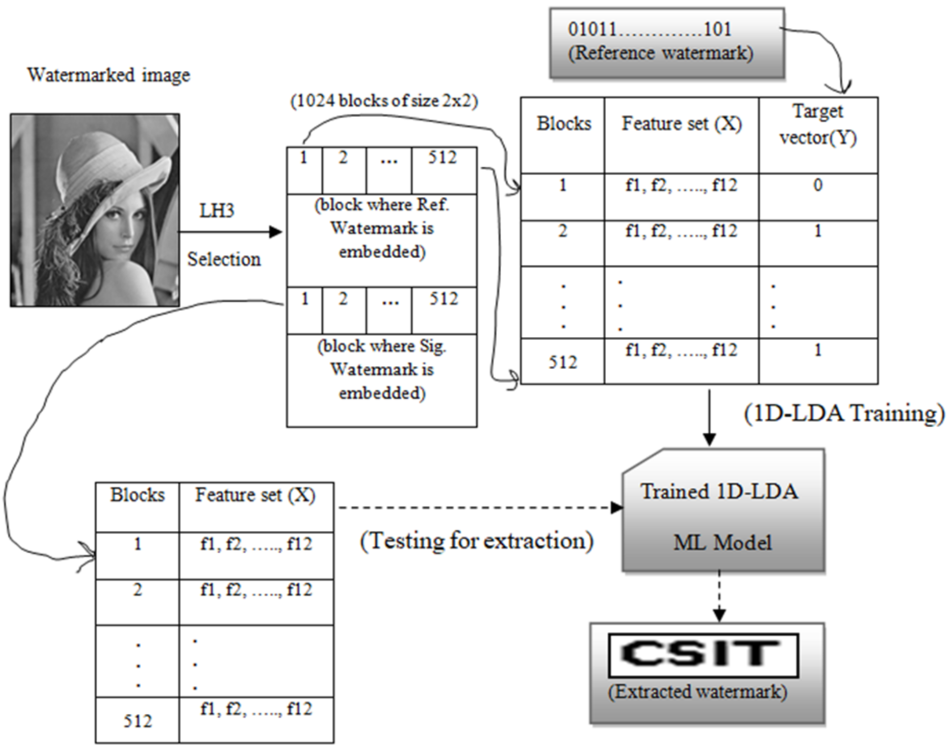

Fig. 2. 1D-LDA ML model training and testing process

Here the original cover image is not needed for watermark extraction. As discussed earlier, the two types of watermarks, a reference watermark and a signature watermark, are embedded in the LH3 sub-bands having a length of 1024 blocks. Initially, 512 bits of reference watermark are embedded into the first 512 blocks of LH3 sub-bands using quantization. Then 512 bits of the remaining signature watermark are embedded into the other 512 blocks of LH3 sub-bands using quantization. Then different statistical features such as Kurtosis (f1), Skewness (f2), Entropy (f3), Standard deviation (f4), Mean (f5), Variance (f6), Mode (f7), Median (f8), Covariance (f9), Poisson probability distribution (f10), Moment (f11), and Quartiles (f12) value of all the corresponding blocks of LH3 are calculated to form a feature set of size 512*12 and then these feature set (f1, f2, ……………, f12) is given for reducing the feature set using the PCA. The outcome of the PCA is a feature set (f1, f2, …….fn) where n is a total number of reduced feature and $n<12$, so in this way, PCA reduce the feature and the size of the obtained feature set is 512*6, then the corresponding coefficient of blocks are added to the feature vector to make it size of (512*10) and then finally one target variable is added as LDA is of supervised nature. The training pattern is generated from the 512 LH3 blocks where the reference watermark is added, and similarly, the testing pattern is generated from the LH3 block where the signature watermark is embedded. The LDA can be trained using the training set, and once the model is trained, it is utilized to test the model for extracting the watermark using the concept of binary classification.

The steps for the watermark extraction are as follows:

Step 1: For LWT based watermarking scheme, obtain the 3rd level LH3 sub-band of watermarked image (512*512) using LWT transform as done in the embedding process. OR

For DWT+LWT based scheme first get 2nd level DWT transform of cover image then get next one level LWT transform.

Step 2: Re-shuffle coefficient of LH3 sub-bands using same secret seed key K1 and blocks using same seed key Key2.

Step 3: Generate feature set $\left(\{fs_i(k)\,|\,k=1,2,\ldots\ldots N\}\right)$ of such blocks where the reference watermark information is embedded.

Step 4: Apply PCA for obtaining the reduced feature set $\left(\{Fsr_i(k)\,|\,k=1,2,\ldots\ldots M\}\right)$ where $M \le N$

Step 5: Add the coefficients and embedding bits (desired output W_i) of the corresponding blocks in order to make training features set φ of size (512*11).

$$\varphi=\{\left(fsr_i(1), fsr_i(2),\ldots\ldots\ldots, fsr_i(M), C_i(1), C_i(2),\ldots., C_i(4)\right), W_i | i=1,2,\ldots\ldots, l_r\} \tag{7}$$

Where $fsr_i(1), fsr_i(2),\ldots\ldots, fsr_i(M)$, are reduced feature set, $C_i(1), C_i(2),\ldots., C_i(4)$ are the coefficients value of corresponding ith blocks, and W_i is the desired output for $i=1,2,\ldots\ldots, l_r$

Step 6: Train the 1D-LDA model using training pattern set and get the trained model LDA_{trn}

Step7: construct the testing pattern set φ' same as training pattern using the blocks where the signature watermark bits are embedded of size (512*10)

$$\varphi'=\{\left(f_i'(1), f_i'(2),\ldots\ldots\ldots, f_i'(M), C_i'(1), C_i'(2),\ldots., C_i'(4)\right) | i=1,2,\ldots\ldots, l_s\} \tag{8}$$

Step 8: Test the model LDA_{trn} using the testing pattern set and extracts the watermark w'.

Step 9: Using seed key K3 reshuffle the w' and reshape w' into the original logo watermark size.

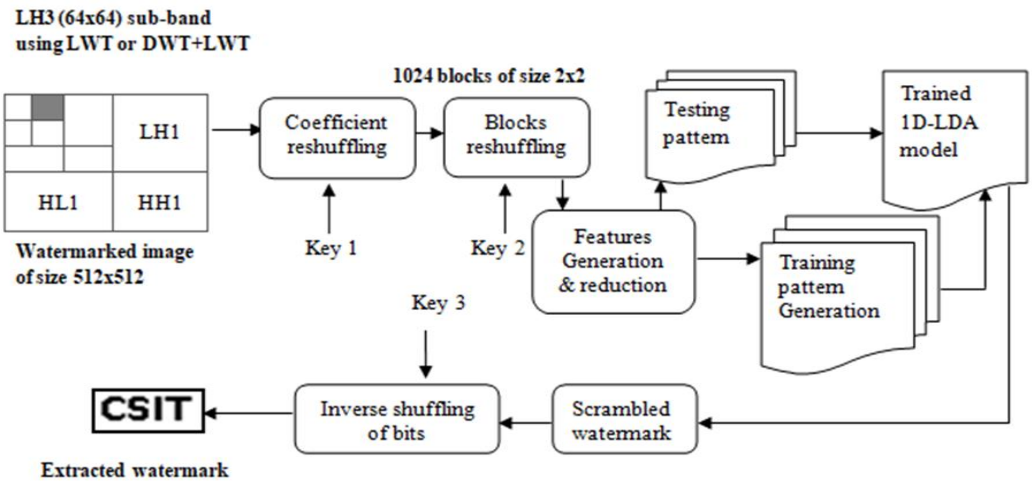

Fig. 3. Watermark extraction procedure

4. Result and Discussion

This section of the paper shows the results and discussion of the proposed work. As stated earlier, one of the challenges of image watermarking is to maintain a reasonable balance between the imperceptibility and robustness of the watermarked image; therefore, an analysis has been carried out as per figure 7 to see what value of threshold full-fills the above requirement and it is found that T=10 is suitable for the experiment purpose. For the research, fifteen standard grayscale images, including Lena, Peppers, and Mandril of size 512*512, 8 bit/pixel and one binary image of size 32*16 are used. The experiment is done on Matlab (2016a) using windows 10. The system used for the experiment is a Lenovo laptop with an Intel i5 processor with 16 GB of RAM. Figure 4 shows the standard image used for the experiments, and all images are taken from the dataset available at [32]. The PSNR value for different threshold values ranging from 8 to 12 on standard images Lena, Peppers, Mandril and Lake is shown using figure 5. Figure 6 contains the original cover image, watermarked image with corresponding PSNR value and extracted watermark image. The mean square error (MSE) between the original CI (cover image) and WI (watermarked image) is obtained using

$$MSE = \frac{1}{M*N}\sum_{ij=0}^{MN} CovImg(i,j) - WatImg(i,j) \tag{9}$$

Where M*N shows the dimension of the images and CovImg(i, j) and WatImg(i, j) represents the grey value at position (i, j). The PSNR can be represented as:

$$PSNR = 10log_{10}\frac{255^2}{MSE} \tag{10}$$

NC value and BER value can be calculated as follows:

$$NC = \frac{\sum_i W_{ij} \sum_j W'_{ij}}{h*w} \tag{11}$$

W_{ij} and W'_{ij} are valued at (i, j) of cover and watermarked image, and it is set as 1 if it is a watermark bit 1; otherwise, it is set as -1; h and w are watermark image dimensions, respectively.

$$BER = \frac{B}{h*w} \tag{12}$$

Where B equal to the wrongly detected bit, and h* w is the dimension.

(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

Fig. 4. Test image (a) Lena, (b) Mandril, (c) Peppers, (d) House, (e) Man, (f) Jetplane, (g) Cameraman, (h) Lake, (i) Livingroom, (j) Walkbridge, (k) Boat, (l) Woman, (m) Satellite, (n) Chest X-ray, and (o) Galaxy

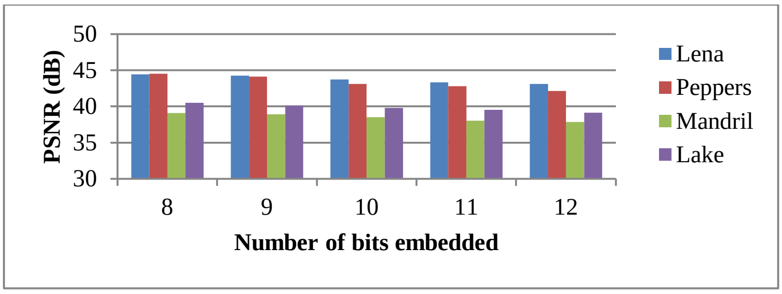

Fig. 5. PSNR (dB) for different threshold value

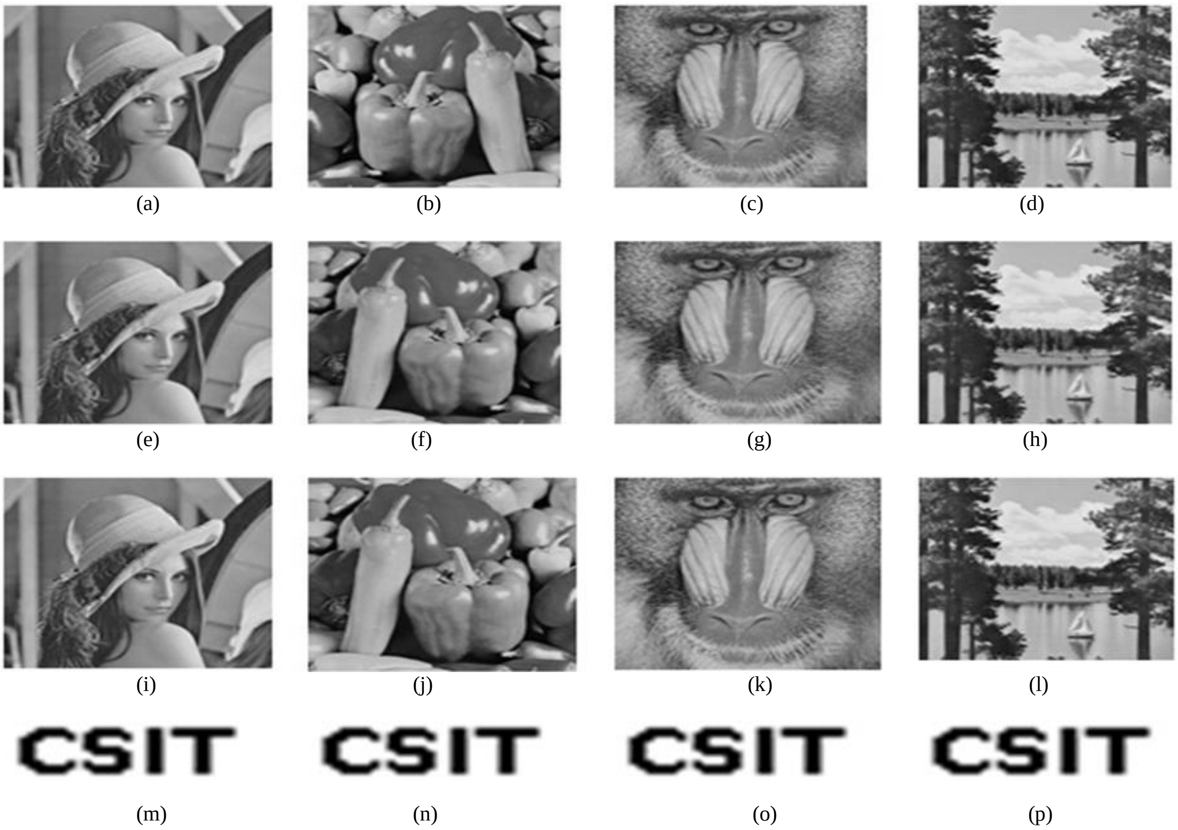

Fig. 6. Original cover image (a) Lena, (b) Peppers, (c) Mandril, (d) Lake, Watermarked image using LWT Scheme (e) Lena with PSNR=43.70 dB, (f) Peppers with PSNR=43.09dB, (g) Mandril with PSNR=35.84dB, (h) Lake with PSNR=36.06dB, Watermarked image using DWT+LWT Scheme (i) Lena with PSNR=44.71dB, (j) Peppers with PSNR=45.05dB, (k) Mandril with PSNR=39.05dB, (h) Lake with PSNR=37.29dB, Extracted watermark (m) – (p) with NC=1 and BER=0

A. *Selection of embedding threshold value*

In the proposed watermarking method the range of threshold value is ranging from 8 to 12 and the selection of the threshold is done as per the figure 7. For finding the best threshold value, a watermarked image is altered using various attacks and then the watermark is extracted. NC value is computed using the extracted watermark and original watermark image. PSNR value is also computed for watermarked image and best threshold value, which show the good balance between robustness and imperceptibility. Instead of selecting the threshold value using the trial and error method, here selection is done using the figure 7.

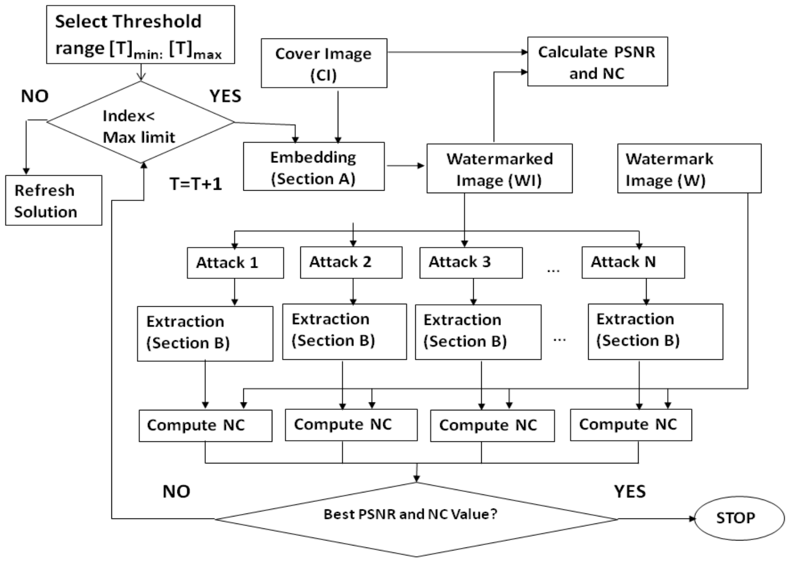

Fig. 7. Selection of embedding threshold value

Watermarked image is measured in terms of Imperceptibility and it is measured using PSNR and the resistance against various attacks is robustness and is measured using NC and BER. In this work PSNR, NC and BER are used to analyse and evaluate the performance of the proposed scheme. PSNR is measure between the cover image and watermarked image and NC and BER is calculated between extracted and original watermark.

B. *Imperceptibility test*

This section of the paper contains the imperceptibility test for both proposed scheme (i.e. LWT and DWT+LWT). Imperceptibility shows the quality of watermarked image and it is measured using PSNR value. Figure 8 shows the PSNR (dB) for fifteen standard images using the LWT based decomposition, and it clearly shows that the proposed watermarking scheme is exhibiting good imperceptibility in terms of PSNR (in dB). Figure 9 shows the PSNR (dB) for fifteen standard images using the DWT+LWT based scheme (where the cover image is processed up to the second level using DWT and then processed up to next one level using LWT). It is found that the second approach (DWT+LWT) method shows the good imperceptibility then the first approach (LWT). Table 1 show the comparison in terms of other existing watermarking methods and one can observe that for the DWT+LWT scheme the robustness is higher as compared to LWT based scheme, this is because of involvement of DWT in the watermark embedding process.

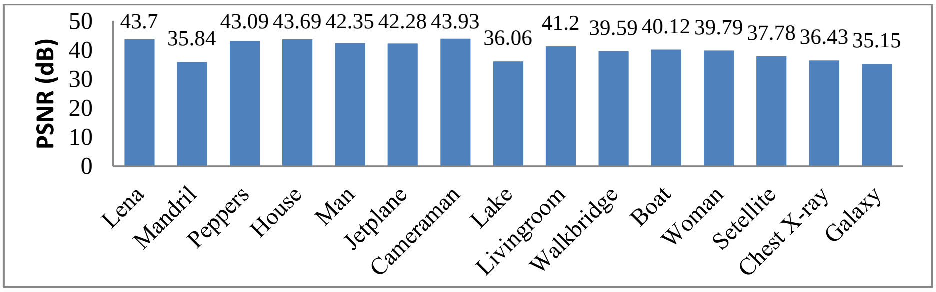

Fig. 8. PSNR of 15 standard images using LWT

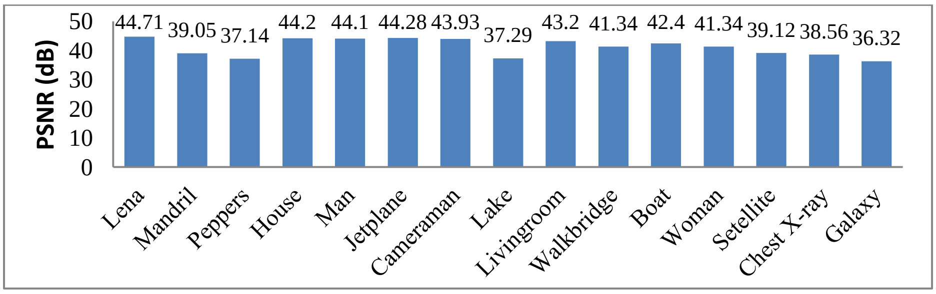

Fig. 9. PSNR of 15 standard images using DWT+LWT

Talbe 1. Comparison with other similar method in terms of imperceptibility (in dB) for Lena image

[17] (LWT+SVM)	[34] (DWT+SVD)	[35] (LWT)	[36] (LWT+SVD+SVM)	**Proposed scheme**	
				LWT based	DWT+LWT based
41.51	47.63	41.40	43.67	43.70	44.71

C. Robustness test

In this section of the paper robustness of the system is evaluated. Robustness is the measure of strength against various image attacks. In the proposed method various image attacks like Cropping (CR), Gaussian Noise (GN), Salt and pepper (SLP), Histogram equalization (HE), Rotation (RT), Speckle noise (SPLN), Scaling (SCL), Median filter (MD), and Jpeg Compression (Jpeg) attack have been considered. In the proposed scheme the watermark extraction is shown as a classification problem therefore the efficiency of model can be estimated in terms of classification rate using the following given formula

$$CR = \frac{S1}{S2} * 100 \tag{13}$$

Where S1 is the total number of instances correctly classified and S2 is the total number of classes. Table 2 shows the performance of the system under various attacks on Lena image for LWT and DWT+ LWT based scheme and one can observe that LWT based scheme perform good as compare to DWT+LWT based scheme therefore all the results have been shown for LWT based scheme.

Talbe 2. Results of test image Lena against various image attacks

Attacks	PSNR (in dB)	LWT				DWT + LWT			
		NC	BER	Classification Rate (CR)	Extracted watermark	NC	BER	Classification Rate (CR)	Extracted watermark
CR (10%)	23.34	0.9493	0.0254	97.46		0.9023	0.0525	92.45	
CR (20%)	21.46	0.8750	0.0625	93.75		0.8515	0.0722	89.21	
CR (25%)	20.12	0.8281	0.0859	91.40		0.8240	0.0878	85.43	
CR (50%)	17.86	0.7031	0.1484	85.15		0.7132	0.1470	87.21	
SLP (0.01)	33.42	0.9765	0.0117	98.72		0.9248	0.0351	95.21	
SLP(0.02)	31.23	0.9531	0.0234	97.92		0.9196	0.0254	93.32	
SPLN (0.01)	32.94	0.9648	0.0175	98.20		0.9270	0.0344	97.56	
SPLN(0.02)	30.45	0.9375	0.0312	96.32		0.9096	0.0488	92.12	
MD (3x3)	37.23	0.9648	0.0175	98.20		0.9375	0.0312	96.32	
GN (0.01)	32.21	0.8242	0.0878	91.40		0.8203	0.0851	92.70	
SCL (0.5)	35.25	0.8829	0.0585	93.95		0.8721	0.0585	93.80	
RT(0.1)	30.12	0.9843	0.0078	99.21		0.9609	0.0172	97.89	
HE	23.42	0.9492	0.0253	97.46		0.9570	0.0214	98.10	
Average NC/BER/CR		*0.9072*	*0.0463*	*95.31*		*0.8861*	*0.0551*	*93.79*	

Talbe 3. NC value of extracted watermark against different image attacks

Images	Image Attacks									
	CR (10%)	CR (20%)	CR (25%)	CR (50%)	GN (0.01)	GN (0.02)	SLP (0.01)	SLP (0.02)	HE	RT (0.1)
Lena	0.9493	0.8750	0.8281	0.7031	0.8242	0.6923	0.9765	0.9531	0.9492	0.9843
Peppers	0.9106	0.8923	0.8723	0.7432	0.8789	0.6835	0.9531	0.9335	0.9687	0.8945
Mandril	0.9012	0.8814	0.8734	0.7421	0.8604	0.6736	0.9462	0.9121	0.9438	0.9456
Lake	0.9023	0.8723	0.8634	0.6034	0.8562	0.6821	0.9545	0.9245	0.9545	0.9612
Cameraman	0.9134	0.9045	0.8825	0.7835	0.8843	0.7026	0.9542	0.9234	0.9520	0.9536
House	0.9231	0.9056	0.8703	0.6704	0.8921	0.7480	0.9654	0.9423	0.9641	0.9460
Man	0.9023	0.8750	0.8217	0.6302	0.9020	0.6121	0.9534	0.9412	0.9712	0.9512
Jetplane	0.8412	0.7734	0.7312	0.6855	0.8723	0.5425	0.9234	0.9102	0.9520	0.9511
Walkbridge	0.9121	0.8723	0.8423	0.6790	0.8578	0.6364	0.9104	0.8945	0.9419	0.9102
Livingroom	0.8903	0.8667	0.8213	0.6530	0.8312	0.6140	0.8904	0.8793	0.9312	0.8902
Boat	0.9145	0.8745	0.8346	0.6243	0.8467	0.4256	0.8956	0.8423	0.9234	0.9034
Woman	0.9434	0.8875	0.8234	0.6439	0.8678	0.5465	0.9067	0.8534	0.9167	0.9123
Satellite	0.9278	0.8948	0.8459	0.6359	0.8956	0.5742	0.9145	0.8756	0.9456	0.9234
Galaxy	0.8854	0.8654	0.8470	0.6179	0.8945	0.5743	0.9126	0.8712	0.9516	0.9189
Ch. X-ray	0.9045	0.8868	0.8579	0.6245	0.8816	0.6679	0.9236	0.8634	0.9513	0.9245

Talbe 4. NC value of extracted watermark against different image attacks

Images	Image Attacks									
	RT (0.2)	SPLN (0.01)	SPLN (0.02)	SPLN (0.05)	SCL (0.5)	SCL (0.9)	SCL (1.5)	MD (2x2)	MD (3x3)	MD (5x5)
Lena	0.9132	0.9648	0.9375	0.7823	0.8829	0.8256	0.7984	0.9745	0.9652	0.8007
Peppers	0.8734	0.9257	0.9218	0.6562	0.9748	0.9660	0.9325	0.9179	0.9258	0.9609
Mandril	0.9234	0.9178	0.9023	0.8608	0.9888	0.9626	0.9425	0.9163	0.9067	0.8904
Lake	0.9456	0.9342	0.9121	0.7612	0.9492	0.9432	0.9212	0.9231	0.9141	0.8823
Cameraman	0.9467	0.9465	0.9325	0.8204	0.9345	0.9287	0.9214	0.9423	0.9132	0.8934
House	0.9230	0.9589	0.9412	0.8312	0.9218	0.9103	0.8902	0.9512	0.9067	0.8830
Man	0.9367	0.9215	0.9045	0.7869	0.9120	0.9034	0.8878	0.9312	0.9056	0.8790
Jetplane	0.9320	0.9532	0.9467	0.7612	0.9492	0.9078	0.8876	0.9320	0.9170	0.8845
Walkbridge	0.8960	0.9432	0.9270	0.8046	0.9503	0.9304	0.9034	0.9215	0.8904	0.8834
Livingroom	0.8602	0.9360	0.9168	0.7212	0.9321	0.9178	0.8945	0.9412	0.9167	0.8912
Boat	0.8859	0.9456	0.9256	0.8045	0.9256	0.9160	0.8956	0.9678	0.9245	0.8934
Woman	0.8946	0.9612	0.9389	0.8178	0.9356	0.9145	0.8878	0.9540	0.9349	0.8821
Satellite	0.9037	0.9581	0.9270	0.7904	0.9257	0.9002	0.9125	0.9423	0.9112	0.8923
Galaxy	0.9089	0.9468	0.9257	0.6079	0.9159	0.8904	0.8623	0.8834	0.8512	0.8734
Ch. X-ray	0.9009	0.9320	0.9145	0.7679	0.9212	0.8821	0.8456	0.8642	0.8329	0.8423

Talbe 5. NC value of extracted watermark against compression attack

Images	Image Attacks							
	Jpeg (80)	Jpeg (70)	Jpeg (60)	Jpeg (50)	Jpeg (40)	Jpeg (30)	Jpeg (20)	Jpeg (10)
Lena	1	1	1	0.9492	0.9214	0.9023	0.8710	0.8523
Peppers	1	1	1	0.9765	0.9531	0.8906	0.8944	0.7578
Mandril	1	1	1	0.9834	0.9667	0.9214	0.9045	0.8453
Lake	1	1	0.9623	0.9424	0.9324	0.8912	0.8725	0.8432
Cameraman	1	1	0.9432	0.9213	0.9145	0.8812	0.8634	0.8420
House	1	1	0.9369	0.9237	0.9189	0.8945	0.8790	0.8562
Man	1	1	0.9453	0.9356	0.9245	0.9034	0.8830	0.8615
Jetplane	1	1	0.9320	0.9219	0.9178	0.8970	0.8754	0.8540
Wallbridge	1	1	0.9412	0.9210	0.9189	0.9034	0.8869	0.8423
Livingroom	1	1	0.9767	0.9612	0.9456	0.9212	0.9034	0.8854
Boat	1	1	0.9524	0.9456	0.9345	0.9134	0.8904	0.8530
Woman	1	1	0.9634	0.9529	0.9422	0.9078	0.8850	0.8420
Satellite	1	1	0.9570	0.9439	0.9212	0.9103	0.8945	0.8120
Galaxy	1	1	0.9469	0.9347	0.9156	0.8945	0.8467	0.8231
Ch. X-ray	1	1	0.9634	0.9467	0.9516	0.9256	0.8902	0.8670

Table 3, 4 and 5 contains the NC value for fifteen standard images against various image attacks. It has been found that the proposed watermarking method is performing well against most of the image attacks.

D. Capacity test

The proposed system is also evaluated for the embedding capacity of the watermark image in the original cover image. The embedding capacity is evaluated as bit per pixel of watermark image inserted into the cover image. In the proposed watermarking method the binary watermark image of size 16*32 is inserted into grayscale cover image of size 512*512, 8 bit/per pixel. The embedding capacity is evaluated as

$$(16*32) / (512*512) = 0.0020 \text{ bit per pixel}$$

E. Security test

The proposed system uses the seed keys at various levels to scramble the bits for enhancing the security of the system. The use of seed keys at embedding steps improves the security of the system. While for watermark extraction, the same secret seed key is used for extracting the watermark.

F. Execution time

The proposed watermarking system is implemented using MATLAB 2016a and a Lenovo laptop with an Intel i5 processor with 16 GB of RAM is used for the experiment purpose. The time complexity includes the embedding and extraction time. Furthermore the execution time also depends upon other factors like the dimension of the test image, system available resources etc. The execution time is measured in terms of second.

Talbe 6. Comparison of average execution time with other methods

Method	[33]	[34]	**Proposed**	
			LWT based	DWT+LWT based
Total time taken	23.41 Sec	16.36 Sec	9.42 Sec	16.81 Sec

Table 6 shows the comparison in terms of average execution time with another similar method. The proposed method uses the LWT in the first scheme and DWT+LWT in second scheme for decomposition of cover image therefore the time taken for embedding and extraction is less than the [33] and [34] for the first scheme because DWT is used in [33] and [34] which takes more time then the LWT.

G. Comparative study

In this section of the paper, the proposed method (LWT based) is compared with some other existing similar methods in terms of NC value on different image against various image attacks.

Talbe 7. Comparison of results with [17], [35] and [36] for different attacks in terms of NC

Attacks	Lena				Peppers			Mandril		
	[17]	[35]	[36]	Proposed	[17]	[35]	Proposed	[17]	[35]	Proposed
SLP(0.01)	0.914	0.753	0.731	**0.9765**	0.91	0.785	**0.9531**	0.929	0.843	**0.9462**
SPLN(0.01)	0.910	0.746	0.738	**0.9648**	0.89	0.80	**0.9257**	0.914	0.800	**0.9178**
SPLN(0.05)	X	X	0.633	**0.7823**	X	X	X	X	X	X
MD (3X3)	0.92	0.95	0.549	**0.9652**	0.918	0.91	**0.9258**	0.898	X	**0.9067**
HE	0.933	0.92	0.98	0.9492	0.937	0.88	**0.9687**	0.895	X	**0.9438**
CR (25%)	X	0.933	X	0.8281	X	0.910	0.8723	X	0.92	0.8734
CR (10%)	0.99	X	0.917	0.9493	0.972	X	0.9106	0.96	X	0.9012
SCL(0.5)	0.94	0.984	0.647	0.8829	0.941	0.97	**0.9748**	0.953	0.964	**0.9888**
SCL(0.9)	0.98	X	X	0.8256	0.964	X	**0.9660**	0.953	X	**0.9626**
JPEG(30)	0.96	0.99	0.945	0.9023	0.945	0.99	0.8906	0.953	X	0.9214
JPEG(40)	0.968	1.0	0.976	0.9214	0.968	0.99	0.9531	0.96	X	**0.9667**
JPEG(50)	0.98	1.0	0.988	0.9492	0.984	1.0	0.75	0.976	X	**0.9834**
JPEG(60)	1.0	1.0	0.991	**1.0**	1.0	1.0	**1.0**	1.0	X	**1.0**

Talbe 8. Comparison of results with [17], [35], and [36] for different attacks in terms of BER

Attacks	Lena				Mandril			
	[17]	[35]	[36]	Proposed	[17]	[35]	[36]	Proposed
SLP(0.01)	0.043	0.048	0.125	**0.011**	0.0352	0.0488	0.1465	**0.027**
HE	0.0332	0.0156	0.002	0.024	0.0257	0.0254	0.0020	0.028
SCL(0.5)	0.0273	X	X	**0.055**	0.0234	X	X	**0.005**
JPEG(30)	0.0195	0.0098	0.025	0.048	0.0234	0.0332	0.052	0.034
JPEG(40)	0.0156	0.0117	0.009	0.034	0.0195	0.0410	0.007	0.025

The comparison of proposed method (LWT based scheme) with other method is shown using table 7 and 8 and it is further noticed that the proposed scheme is performing well against most of the image attacks because of good classification ability of the 1D-LDA and good feature selection using the PCA. The highlighted value shows the given scheme performs well or equal over existing similar scheme and the sign of X shows missing data. Performance comparison with [37] in terms of NC value for standard image peppers is shown using the figure 10. Similarly performance comparison using NC value for Lena standard image with [38] is shown using figure 11. Figure 12 and figure 13 shows the comparison in terms of BER value with [39] for standard image Lena and Peppers respectively. Further figures 14 and 15 shows the comparison in terms of NC value with [40] for Peppers and Mandril image respectively. The figures 10-15 clearly shows that the proposed watermarking method performs better against most of the image attacks in comparison with other state-of-the-art.

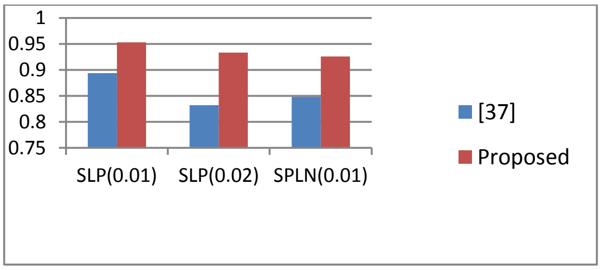

Fig. 10. Performance comparison in terms of NC for Peppers image

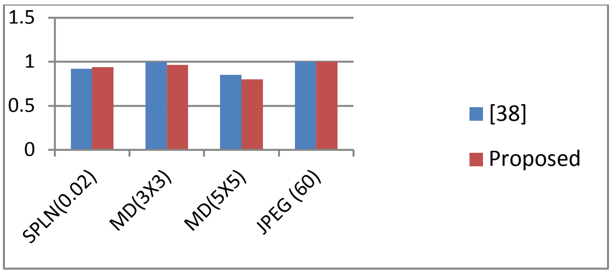

Fig. 11. Performance comparison in terms of NC for Lena image

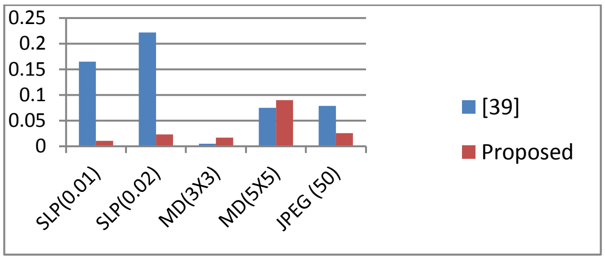

Fig. 12. Performance comparison in terms of BER for Lena image

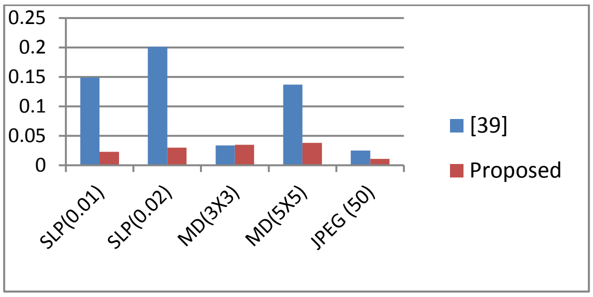

Fig. 13. Performance comparison in terms of BER for Peppers image

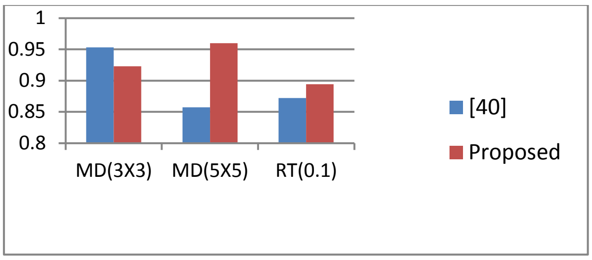

Fig. 14. Performance comparison in terms of NC for Peppers image

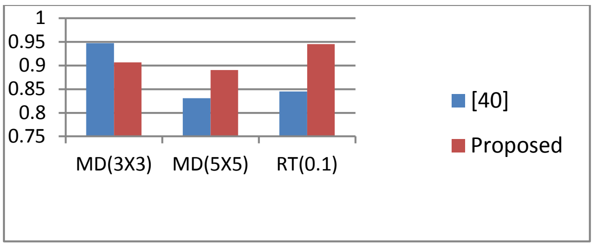

Fig. 15. Performance comparison in terms of NC for Mandril image

5. Conclusion

The digital image watermarking method is essential tools for proving the ownership of the digital image and providing the security to the digital image. One of the challenges of digital image is to maintain the balance in between imperceptibility and robustness. In watermarking process the watermark information is embedded in such a way that the originality of the watermarked image is not distorted at all. The proposed watermarking scheme tries to deal with all these issues by incorporating a novel threshold selection method and involvement of 1D-LDA for watermark extraction. In order to improve the security of the system, various seed keys and Arnold cat map are used at different level of the embedding process. In the proposed method two schemes, i.e. LWT and DWT+LWT based watermarking is used and it is seen that DWT+LWT based watermarking scheme gives good imperceptibility in terms of PSNR, whereas the second scheme based on LWT performs good in terms of the robustness and average time taken for embedding process and extraction process. The efficiency of the LWT makes the LWT based watermarking scheme efficient in terms of average time taken. The performance of the system is presented and compared with other similar existing method, and it is found that the proposed scheme outperform other exiting method. One of the limitations of the proposed watermarking method is that it underperforms in the case of CR (50%) and GN (0.02) attacks and sometimes the selection of threshold value may not be optimal. This idea may be implemented with video and color image watermarking in future.

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