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An imperceptible & robust digital image watermarking scheme based on DWT, entropy and neural network

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Abstract

Due to the unlawful manipulation and image processing attacks, the copyright protection of digital image is paid more and more attention. This paper proposes a digital image watermarking technique to protect image authentication based on discrete wavelet transform (DWT), entropy and neural network. Firstly, the DWT is used to divide the host image and the watermark image into frequency sub-bands. Then, the entropy of each frequency sub-band is calculated to find the maximum entropy sub-band in order to embed the highest entropy sub-band of the watermark image into the highest entropy sub-band of the host image. Finally, the neural network is used for determining the relationship between the pixel values of the host image and the watermarked image which is used later in the watermark extraction process. Moreover, a moving average filter is used prior to the extraction process for reducing the image processing attacks. Performance of the proposed method is tested against different image processing attacks (such as Filtering, Gaussian noise, Rotation, and Cropping). Experimental results demonstrate that this proposed method not only has the superior robustness and imperceptibility but also has improved the anti-attack capability in comparison with recent works in this field.

Keywords

Discrete Wavelet Transform, Entropy, General Regression Neural Network (GRNN), Moving Average Filter, Normalized Correlation (NC)

1. Introduction

The ultimate purpose of any digital watermarking scheme is to safeguard the ownership of data (image, audio, text or video) by hiding information in the original data [1]. Technological growth makes it easier to duplicate the contents of a legal owner without permission. Reasons behind these are the knowledge of the image processing techniques and internet hacking which are available to the illegal parties [1,2]. Various kinds of efficient watermarking schemes have already been proposed by many researchers throughout the world to prevent these illegal actions but they hardly could ensure both imperceptibility and robustness at the same time.

Between the two main properties of an efficient watermarking scheme, the first one is imperceptibility [1]. Imperceptibility means that the watermark image or data should not be noticeable in the host image or cover image. The second property is robustness which means that the secret watermark image must endure the image processing attacks like noise additions, filtering, cropping and rotation [3]. The user needs to compromise between these two properties during the design procedure. All the proposed watermarking techniques fall into two classes called spatial domain techniques and transfer domain techniques respectively.

A large number of techniques have been developed in spatial domain such as the substitution of the least significant bit of images on the basis of maximum entropy [4] and the use of the watermarking coefficients found from quantum type neural networks [5]. The method proposed by RADOUANE et al. [4] shows the gradual degradation of PSNR with more bit substitution because of the bits located in the lower position are randomly inverted. But the scheme developed by Shiyan Hu [5] shows better results as the embedding of the bits are done into the weight-invariant partitions compared to the other bit substitution based methods.

Transform domain-based methods such as discrete wavelet transform (DWT) [6−11] and discrete cosine transform [12,13] hide data by performing operations on the coefficients in the frequency domain using the secret key. These techniques show improved results against the image processing attacks compared to the techniques in the spatial domain. Another technique called Singular Value Decomposition (SVD) based watermarking uses equilateral bases which are not stable [14]. It shows good robustness property but suffers from imperceptibility problem. Cox et al. [3] focus on the perceptual pattern formation for watermarking which is a leading step for efficient watermarking with less visual degradation of the host image.

To improve the performance of digital watermarking, the use of neural networks becomes popular day by day. The initial move toward neural systems came in 1943 when Warren McCulloch, a neurophysiologist, and a mathematician, Walter Pitts, composed a paper on how neurons may function. They demonstrated a basic neural system with electrical circuits [15]. With the progress of neural networks, researchers found advantages of using the neural network in various types of systems to improve the performance [16,17].

Bansal et al. [18] generate network weights from a cover image which are used in the training process of the back-propagation neural network. Later on, these weights are used for watermark extraction. This method has lower PSNR values against different types of attacks. AL-Nabhani et al. [19] use the Haar filter for embedding watermark and probabilistic neural network for watermark extraction. It shows excellent robustness and imperceptibility compared to the conventional transform domain techniques which contain no filter and no neural network. But its performance is reduced when the number of PNN inputs increase as the network does not get enough time to be trained. Uchida et al. [20] embed watermarks using deep neural networks which show that the watermark does not vanish even after the many stages of filtering and calibration. But it suffers from training sample loss and test error during the embedding process. Mamatha and Venkatram utilize 2D Lifting Wavelet Transform (LWT) for medical image watermarking and neural network for security reason [21]. It takes short calculation time in processing and less memory storage but the quality of the recovered image is not so good as the cover image goes through different stages of LWT prior to the extraction process.

On the basis of the limitations of the previous methods, in our research, DWT, maximum entropy selection and a regression neural network are used to improve the watermark performance parameters. The motivation behind the use of the neural network is that it can decrease the execution time compared to the fuzzy approaches [22]. In most cases, increasing the

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delay time makes the system unreliable. Another important feature is that it can easily determine the input−output mapping through a large number of training samples. Compared to other neural networks, the regression neural network contains single pass adaptability so no need to back-propagate. Hence, it needs less time to be trained. Besides, it has high precision in noise handling and estimation of distances.

The remaining parts of the paper are organized as follows: section 2 describes the proposed watermarking method in detail. The equations of the performance parameters are shown in section 3. Section 4 includes the results and analysis of the proposed scheme. Finally, the findings and future scopes of the research are concluded in section 5.

2. Proposed watermarking method

The proposed watermarking scheme can be divided into the following two divisions:

i) Watermark Embedding
ii) Watermark Extraction

2.1. Algorithm of watermark embedding

The flow chart of watermark embedding algorithm is shown in Fig. 1. Original image and the watermark image go through DWT, entropy calculation and sub-band selection steps. Then, Embedding is accomplished

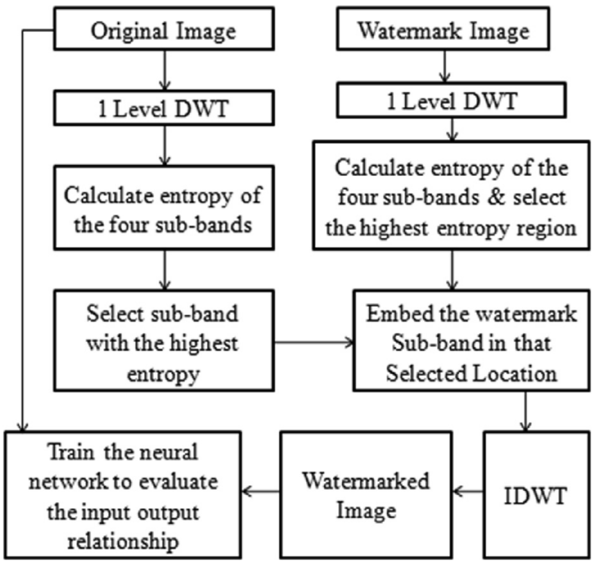

Fig. 1. Flow chart of watermark embedding.

followed by IDWT to get the watermarked image. Finally, the neural network is trained. The whole process can be divided into the following steps:

Step 1: Host image is decomposed into four sub-bands using 1-level DWT. The robustness property may be improved by increasing the number of DWT levels but it can reduce the payload capacity. DWT base function can be defined as [23]:

$$G_{d,t}(m) = \left\{ G\left(\frac{m-d}{t}\right),\ (d,t) \in R\,X\,R^{+} \right\} \tag{1}$$

where G(m) is the mother wavelet function, d is the dilation amount, t is the translation amount and R is the real numbers.

Step 2: Calculate the entropy of the four sub-bands and select the sub-band with the highest entropy. The highest entropy regions show maximum randomness. As a result, embedding in that region does not visually degrade the host image very much. Some more advantages are discussed in section 4.1. The overall entropy calculation can be described as follows:

If each sub-band has an L number of pixels, each has an area of ΔQ and B_j be the average brightness of jth pixel the brightness can be written as:

$$B_j = \frac{E}{\Delta Q} t_j \tag{2}$$

Where E is the energy of the photons in each discrete pixel and t_j is the average number of photons in the jth pixel. The probability of a photon in the jth pixel can be defined as:

$$P_j = \frac{t_j}{\sum_j t_j} \tag{3}$$

Now the entropy of the probability distribution P_j can be written as [24]:

$$\mathcal{E} = -\sum_{j=1}^{L} P_j \log P_j \tag{4}$$

Usually, LL sub-band is not suitable for embedding because it shows low entropy and low-frequency components which contain most of the image information [25]. Besides, it may be influenced by other compression attacks.

Step 3: Watermark image is decomposed into four sub-bands using 1-level DWT.
Step 4: Calculate the entropy of the four sub-bands & select the highest entropy sub-band of the watermark image.
Step 5: Embed the watermark sub-band in the selected sub-band of the host image pixel by pixel.
Step 6: Perform IDWT to get the watermarked image.
Step 7: Train the regression neural network to memorize the characteristics of relations between the watermarked image pixels and the host image pixels. The working principle of the general regression neural network (GRNN) is given below.

GRNN was introduced by Donald F. Specht in 1990 which is a kind of probabilistic neural networks [26]. Sometimes a few training samples are not sufficient enough to converge the system function of an operating system. In that case use of GRNN is the best choice because it needs a few training samples to carry out the predictions.

The probability density function that is utilized in GRNN falls into the category of the normal distribution. In this case, the training sample inputs Xi are the pixels of the host image and Y(X) are the outputs of the network which represents the pixels of the watermarked image. Network function can be written as:

$$Y(X) = \frac{\sum_{i=1}^{n} Yi\ .\ \exp\left(-\frac{Di^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{Di^2}{2\sigma^2}\right)} \quad (5)$$

$$\mathrm{Di}^2 = (\mathrm{X} - \mathrm{Xi})^{\mathrm{T}}.(\mathrm{X} - \mathrm{Xi}) \quad (6)$$

where Yi is the corresponding output for each Xi. The distance between the training sample Xi and the prediction point X is represented by Di. It indicates how close the prediction point is located to the training sample point. If Di is small then $\exp\left(-\frac{Di^2}{2\sigma^2}\right)$ turns into a large value. For Di = 0, $\exp\left(-\frac{Di^2}{2\sigma^2}\right)$ turns into one which shows that X and Xi are super-imposed.

When the distance gets higher, the exponential term turns into a small value. Consequently, the other training pixel samples lead to less impact on the pixel prediction points. The standard deviation σ is a measure of smoothness. If σ becomes large, estimation by the training pixel samples can be done for a broad region of X and vice versa. In this case, the default value σ = 0.1 is used for simplicity.

Fig. 2 shows the construction of GRNN. The first layer operates just like the operation radial basis neural network. Each neuron's weighted input is the distance Di between the prediction point and the training sample. These inputs of first layer neurons are weighted with the corresponding values of Yi. Each net input from the summing junction is passed through the $\exp\left(-\frac{Di^2}{2\sigma^2}\right)$ function while the center of the normal distribution is at each training sample.

The weights on the signals going towards the second layer are one. Then the weighted signals are passed through the same exponential activation function to produce the final output Y(X).

The neural network used in the algorithm has the following advantages over the fuzzy logic based algorithm:

i) Neural Network can learn and show non-direct and complex connections, which is extremely critical in fuzzy logic because huge numbers of the connections among sources of input and output pixels are non-straight and complex.
ii) The neural network can anticipate concealed information more quickly & precisely than fuzzy logic.
iii) The neural network can regenerate the huge amount of data if one or more nodes of the network on the network become disabled. These can be used to make the node working which is not possible with fuzzy logic.

2.2. Algorithm of watermark extraction

The flow chart of the entire algorithm is given in Fig. 3 and can be divided into the following steps:

Step 1: First DWT is applied to the watermarked image.
Step 2: Moving average filter is applied to different sub-bands to minimize image processing attacks. The operation of the moving average filter is given below.

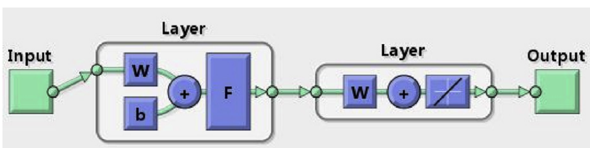

Fig. 2. Architecture of the general regression neural network.

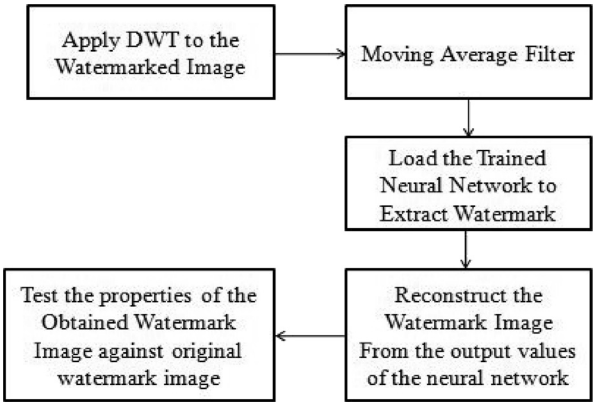

Fig. 3. Flow chart of watermark extraction.

Moving average filter regularize the images by minimizing the degree of intensity difference among the adjoining pixels. When the filter goes through the image pixel by pixel, it substitutes each pixel value with the average value of the adjoining pixels. If a single pixel has an insignificant value, it can degrade the average values in its neighborhood. Again, the filter faces another problem when it operates at the edges of the image, which results in a small scale image blurring. These points should be kept in mind when we are using this filter.

The equation of this filter can be written as below [27]:

$$y[i] = \frac{1}{M}\sum_{j=0}^{M-1} x[i+j] \tag{7}$$

where x[ ] is the input pixel, y[ ] is the output pixel and M is the number of points in the filter. During the operation, it is needed to normalize the pixel values because the pixel values must be kept between 0 and 255 for matching the frame. Hence in our scheme, we should divide each pixel value by 255.

The output pixels contain low-frequency components which indicate that the filter removes high frequencies. Therefore all attacking noises of high frequency are eliminated significantly in the extraction of the watermark image. Besides, the filter performance is improved if the number of points is increased. However, in that case, the image becomes edge sensitive as discussed earlier. In our scheme, a 3 point moving average filter is used.

Step 3: The trained neural network is loaded to extract the watermark from different sub-bands. It contains the relationship distance values between the pixels of host image and watermarked image when it was trained in the watermark embedding phase.

Step 4: The watermark image is reconstructed from the output values of the neural network simulation.

Step 5: The properties of the obtained watermark image are tested against the original watermark image.

3. Performance measuring parameters

The performance of the watermarking scheme is measured according to the following parameters:

i) Mean Square Error (MSE): It compares the cover image and watermarked image pixel by pixel values according to the following equation [28]:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[C(i,j) - W(i,j)]^2 \tag{8}$$

where M X N is the size of the images, C(i,j) is the cover image and W(i,j) is the watermarked image respectively.

ii) Peak Signal to Noise Ratio (PSNR): It evaluates the degradation of the cover image when the cover image is watermarked and it is calculated by the following formula [25]:

$$PSNR = 10\log_{10}\frac{255\,X\,255}{MSE} \tag{9}$$

iii) Normalized Correlation (NC): It shows the degree of similarity between the watermark image and extracted watermark image according to the following equation [29]:

$$NC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\mathrm{W(i,j)E(i,j)}}{\sum_{i=1}^{M}\sum_{j=1}^{N}\mathrm{W(i,j)W(i,j)}} \tag{10}$$

where W(i,j) is the watermark image and E(i,j) is the extracted watermark image respectively.

Fig. 4. Host image.

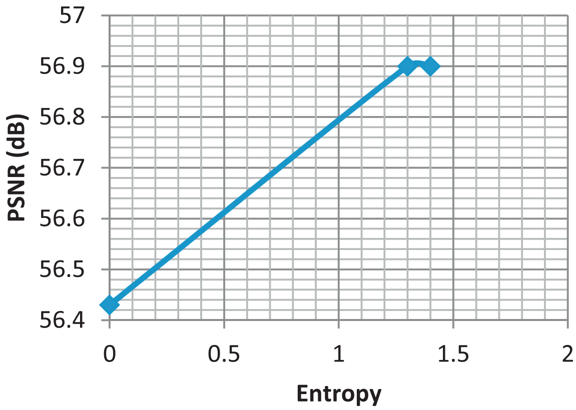

Fig. 6. Entropy vs. PSNR graph for no attack on the images.

4. Results and analysis

In this section, performances of the proposed method are presented. A grayscale “Lena” image of size 512 × 512 is used as host image and a grayscale “Airplane” image of size 512 × 512 is used as the watermark image. Both images are shown in Fig. 4 and Fig. 5 respectively. This adaptive watermarking scheme can also be used for other images as well. Advantages of using entropy in the embedding process are discussed in section 4.1. Then, the performance of the proposed method without and with attacks is analyzed in section 4.2. Finally, a comparison of the proposed methods with some existing methods is discussed in section 4.3.

4.1. Benefits of using entropy in the embedding process

The watermark image had been embedded in the highest entropy region of the host image. In this section, the entropy of the host image is gradually increased and the system performance is monitored. Entropy versus PSNR and Entropy versus NC graphs without any attacks on the images are shown in Fig. 6 and Fig. 7 respectively. It can be observed that with the increase of entropy the PSNR value is rising significantly. Also, the NC value is growing sharply when we are moving towards the maximum entropy region.

Likewise, Entropy versus PSNR and Entropy versus NC graphs for different types of attacks on the images are shown in Fig. 8 and Fig. 9 respectively. Again it can be seen that with the shifting from the minimum entropy region towards the maximum entropy region the PSNR and NC values are upgrading. Another important point found by comparing the graphs with no attacks on the images is that the use of maximum entropy region improves the performance parameters remarkably. Hence, it can be said that the proposed scheme can reduce the image processing attacks with a great margin.

Fig. 5. Watermark image.

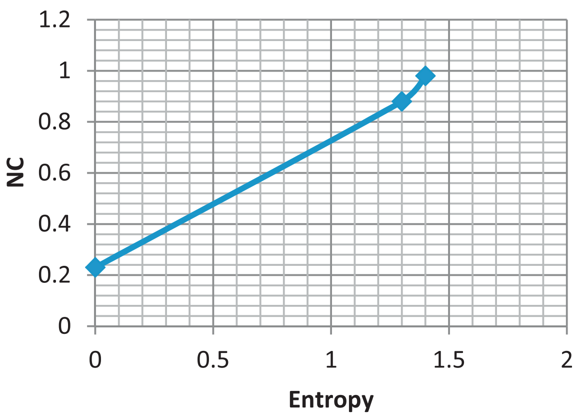

Fig. 7. Entropy vs. NC graph for no attack on the images.

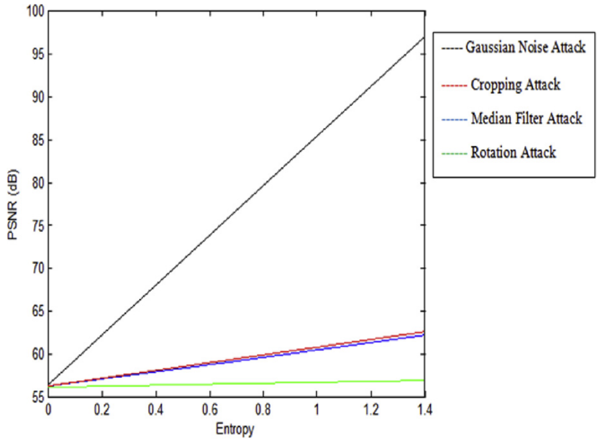

Fig. 8. Entropy vs. PSNR graphs for different types of attack on the images.

4.2. Performance of the proposed method

4.2.1. Without attack

The value of watermark embedding strength α is chosen as 0.9. The watermarked image is shown in Fig. 10. The recovered watermark image from the proposed method without any attack is shown in Fig. 11. The MSE and PSNR value calculated for no attack in the image is 0.1382 and 56.7584 dB respectively. So it can be observed that there is no visual degradation between the host image and watermarked image as the PSNR value is high. Hence, it can be concluded that the proposed method is imperceptible. Also, the NC value determined for no attack in the image is 0.9900.

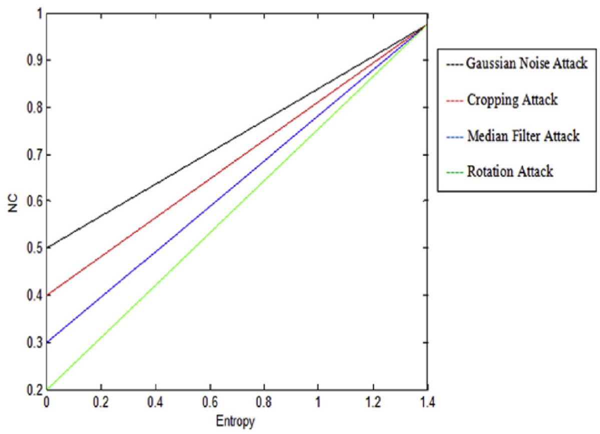

Fig. 9. Entropy vs. NC graphs for different types of attacks on the images.

Fig. 10. Watermarked image.

4.2.2. With attacks

MSE, PSNR and NC values of the proposed method against different types of attacks are shown in Table 1. Exploring the results, it can be concluded that the proposed method has a higher degree of robustness against different types of image processing attacks. Also, the watermark images extracted from the proposed scheme after all kinds of image processing attacks are shown in Fig. 12, Fig. 13, Fig. 14 and Fig. 15 respectively.

4.3. Performance comparison of the proposed method

MSE, PSNR and NC values of the proposed method and different existing methods against various kinds of attacks like Median Filtering, Gaussian noise, Cropping and Rotation are tabulated in Table 2, Table 3, Table 4 and Table 5 respectively. Although the extracted watermark from the proposed scheme has an NC value of 2%−9% smaller than the other references, it does not degrade the watermark very much. Another

Fig. 11. Recovered watermark image without any attack.

Table 1
MSE, PSNR and NC values of the proposed method against different types of attacks on the images.

Type of attack	MSE	PSNR (dB)	NC
Median Filtering	0.0412	62.0186	0.9747
Gaussian Noise	1.3456e-005	96.8756	0.9747
Cropping	0.0365	62.5387	0.9747
Rotation	0.1337	56.9024	0.9747

important point is that the PSNR value of the proposed scheme against Gaussian Noise attack is comparatively higher than other methods. The reason behind this is the use of regression neural network which improves the pixel values of the watermarked image.

Fig. 16 and Fig. 17 show the comparison of different methods on the basis of average PSNR and NC values for various types of attacks. It can be seen that the proposed method has higher PSNR than the other methods. Although the NC value of the method proposed in Ref. [30] is 0.4% higher than our proposed method, however, ref. [30] has a 80% lower PSNR value than ours.

Fig. 12. Extracted watermark image after Median Filtering attack.

Fig. 13. Extracted watermark image after Gaussian Noise attack.

Fig. 14. Extracted watermark image after cropping attack.

Fig. 15. Extracted watermark image after 43° Rotation attack.

Table 2
MSE, PSNR and NC values of different methods after Median filtering Attack on the images.

Watermarking Scheme	MSE	PSNR (dB)	NC
Ref. [25]	–	48.2500	0.8700
Ref. [28]	–	–	–
Ref. [30]	–	21.1087	0.9800
Ref. [31]	–	–	–
Ref. [32]	–	–	–
Ref. [33]	–	–	–
Ref. [34]	–	30.6025	0.9713
Proposed Method	0.0412	62.0186	0.9747

Table 3
MSE, PSNR and NC values of different methods after Gaussian noise Attack on the images.

Watermarking Scheme	MSE	PSNR (dB)	NC
Ref. [25]	–	48.2500	0.9200
Ref. [28]	0.3954	52.1940	–
Ref. [30]	–	21.6222	0.9800
Ref. [31]	1.5247	49.8650	–
Ref. [32]	0.0034	28.7120	–
Ref. [33]	–	20.2585	0.9592
Ref. [34]	–	24.2990	0.7186
Proposed Method	1.3456e-005	96.8756	0.9747

Table 4
MSE, PSNR and NC values of different methods after Cropping Attack on the images.

Watermarking Scheme	MSE	PSNR (dB)	NC
Ref. [25]	–	48.2500	0.9900
Ref. [28]	–	–	–
Ref. [30]	–	9.0585	0.9766
Ref. [31]	–	–	–
Ref. [32]	–	–	–
Ref. [33]	–	19.5078	0.9515
Ref. [34]	–	43.9137	0.9734
Proposed Method	0.0365	62.5387	0.9747

Table 5
MSE, PSNR and NC values of different methods after 43° Rotation Attack on the images.

Watermarking Scheme	MSE	PSNR (dB)	NC
Ref. [25]	–	48.2500	0.9000
Ref. [28]	–	–	–
Ref. [30]	–	2.9243	0.9795
Ref. [31]	–	–	–
Ref. [32]	–	–	–
Ref. [33]	–	20.7802	0.9636
Ref. [34]	–	30.5623	0.9445
Proposed Method	0.1337	56.9024	0.9747

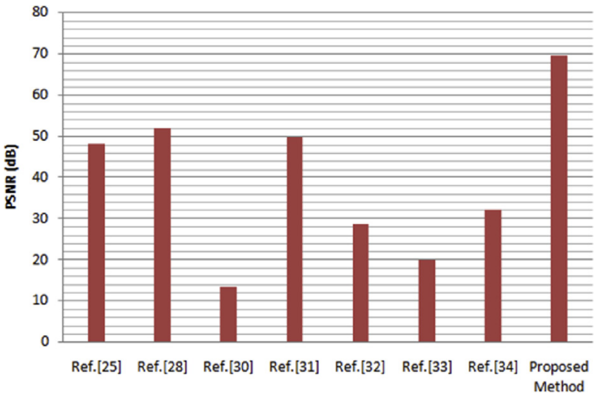

Fig. 16. Comparison of different methods on the basis of the Average PSNR values for various types of attacks.

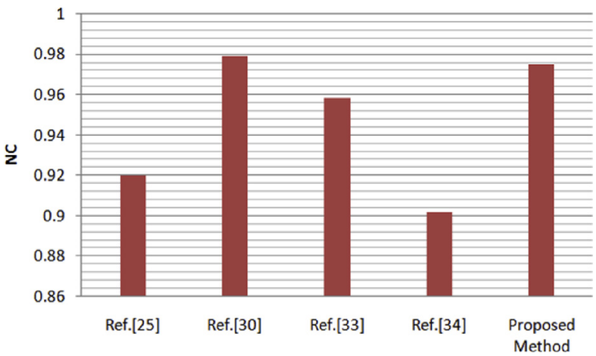

Fig. 17. Comparison of different methods on the basis of the Average NC values for various types of attacks.

5. Conclusion

In this paper, a digital image watermarking method based on DWT, entropy & neural network has been proposed. DWT is used for dividing the image into sub-bands and then the entropy is calculated to find the maximum entropy region as it is low information area. Therefore, adding watermark pixels in that region do not degrade the cover image very much. Also, the regression neural network modifies the distance values on the basis of prediction point locations and thus makes an efficient relationship between the input and output pixels when it is trained. This trained network containing the relationship weight values is utilized in the watermark extraction process. It can hide digital information securely than fuzzy based methods because the neural network can determine the non-linear complex connections among the pixel more precisely. In addition, the moving average filter which is incorporated in the watermark extraction process, increase the performance of the extraction process by minimizing the unwanted noise attacks. The scheme shows better PSNR and NC values, which are the indication of improved robustness and imperceptibility. From the extracted watermark images it can be seen that if a watermarked image is suspected to image processing attacks, the proposed scheme can reduce it & extract the hidden watermark image. The proposed system shows the execution time is 4.20084 s in MATLAB 7.6.0 (R2008a) version for Windows 7 operating system. So, it needs proper entropy matching pursuit and the nonlinear estimate of deep architecture for implementation. In the future, the watermark extraction process can be investigated more to increase the NC values and the performance of other neural networks can also be analyzed in place of the regression type. Besides, application of this algorithm in medical image processing for information security and switching among the other entropy regions for a new hybrid algorithm can be analyzed for different activation functions in the neural network.

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