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A New Robust Digital Image Watermarking Technique Using Relations between Wavelet Coefficients Transform and Full Counter Propagation Neural Network

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***Abstract*: This paper presents a new robust digital image watermarking technique based on relation between wavelet coefficients transform and neural network. The neural network is Full Counter propagation Neural Network (FCNN). FCNN has been used to simulate the perceptual and visual characteristics of the original image. The perceptual features of the original image have been used to determine the highest changeable threshold values of DWT coefficients. The highest changeable threshold values have been used to embed the watermark in DWT coefficients of the original image. The watermark is a binary image. The pixel values of this image are inserted as zero and one values in the DWT coefficients of the image. The implementation results have shown that this watermarking algorithm has excellent robustness versus different kinds of watermarking attacks.**

***Keywords:* Digital Image Watermarking, Discrete Wavelet Transform, Neural Network, Human Visual System.**

1. INTRODUCTION

Owing to the popularity of the Internet, the use and transfer of digitized media are increasing. However, this frequent use of the Internet has created the need for security. It is imperative to protect information to prevent intentional or unwitting use of information by someone other than the rightful owner. A commonly used method is to insert watermarks into original information to declare rightful ownership. This is the so-called watermarking technique. A watermark can be a visible or invisible text, binary stream, audio, image, or video. It is embedded in an original source and is expected to tolerate attacks of any kind. A valid watermarking procedure enables one to judge the owner of media contents via a retrieved watermark even if it is attacked and is, thus, fragmentary [1].

A trustworthy and effective watermarking algorithm should consider the following:

Transparency: The embedded watermark in the image should be perceptually and visually imperceptible. This requirement holds the most challenges for the images having noticeable pixel similarities in different parts of the image.

Robustness: A secure watermark should be difficult to remove or destroy, or at least the watermarked image must be severely degraded before the watermark is lost. Typical intentional or unwitting attacks include:

Common digital processing: A watermark should survive after image blurring, compression, dithering, printing and scanning, etc.

Subterfuge attacks (collusion and forgery) [15]: A watermark should be resistant to combinations of the same image watermarks (collusion). In addition, a watermark should be robust to repeated watermarking (forgery).

Geometric distortions: A watermark should be able to survive attacks which use general geometric transformation, such as cropping, rotation, translation, and scaling.

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Capacity: The watermark capacity includes the discussions and techniques which provide the image with possibility to embed the majority of information [2]. This paper doesn't emphasis on this watermarking discussion.

Blind Watermarking: Extracting watermark from the watermarked image, without using original image, is considerable for a variety of reasons: in some cases, it is impossible to avail the original image; searching for the original image in digital library is time consuming and costly [1].

In terms of embedding data in the image the watermarking algorithms are divided into two groups of spatial and frequency domain methods [3]. Spatial domain methods embed the data in brightness or color of image. Spatial domain methods have advantage of being more consistent with HVS model, but its disadvantages are the sensitivity to the image resizing, cropping, and the other performable geometric operations on the image. Frequency domain methods mainly include DCT, DFT (Discrete Fourier Transform), and DWT (Discrete Wavelet Transform).

Wavelet plays a more and more important role in contemporary image processing field. It has lots of special advantages that conventional transforms, such as DCT and DFT, cannot achieve. Furthermore, it has become the fundamental transform in JPEG2000 standard. Wavelet transform can make localizing analysis of frequency in space and time domain. It gets image multi-scale details step by step via flexing and parallel moving operation where time details at high frequencies part and frequency details at low frequencies part. As scale becomes smaller, every part gets more accurate, and ultimately all image details can be focalized accurately [9]. Discrete wavelet transform is made to input image, it will produce three high frequency parts (HL, LH and HH) and one low frequency part (LL). (Fig.1)

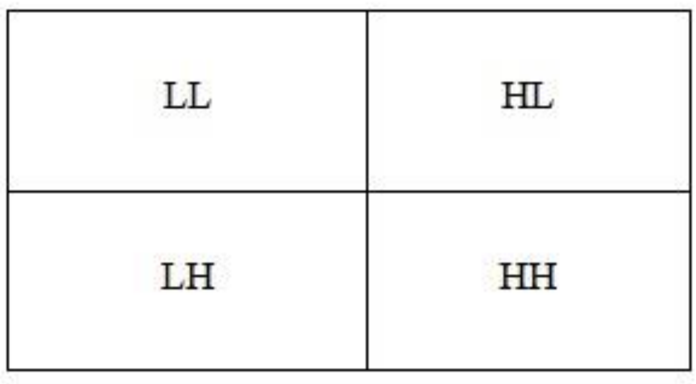

Fig 1: One Decomposition Level of Wavelet Coefficients structure

The low frequency part can denote optimal approach to original image with the largest scale and the lowest resolution that determined by wavelet analysis progression. Its statistical character is similar to original image one and the majority of image energy concentrate in here. The high frequency parts denote detail information in the diverse scales and resolution. As resolution is lower, the proportion of available information is larger. That is to say, an image is divided into some classes. In the same class, the low frequency sub image (LL) has highest energy, HL, LH, HH follow on the heels in turn. For different classes, the higher one has more energy. [9] The Three decomposition level wavelet transform coefficients organization are shown in Fig.2. Wavelet transform decomposes an image into a set of hand limited components which can be reassembled to reconstruct the original image without error. Since the bandwidth of the resulting sub bands is smaller than that of the original image, the sub bands can be down sampled without loss of information. Reconstruction of the original signal is accomplished by up sampling, filtering and summing the individual sub hands. For our purpose, an image is first decomposed into four parts of high, middle, and low frequencies (i.e., LL1, HLl, LH1, HH1 sub bands) by down sampling horizontal and vertical channels using sub band filters. The sub bands labeled HLl, LH1, and HH1 represent the fine scale wavelet coefficients. To obtain the next coarser scaled wavelet coefficients, the sub hand LL1 is further decomposed and critically down sampled. This process is repeated several times, which is determined by the application in hand. An example of an image being decomposed into ten sub bands for three levels is shown in Fig.2.

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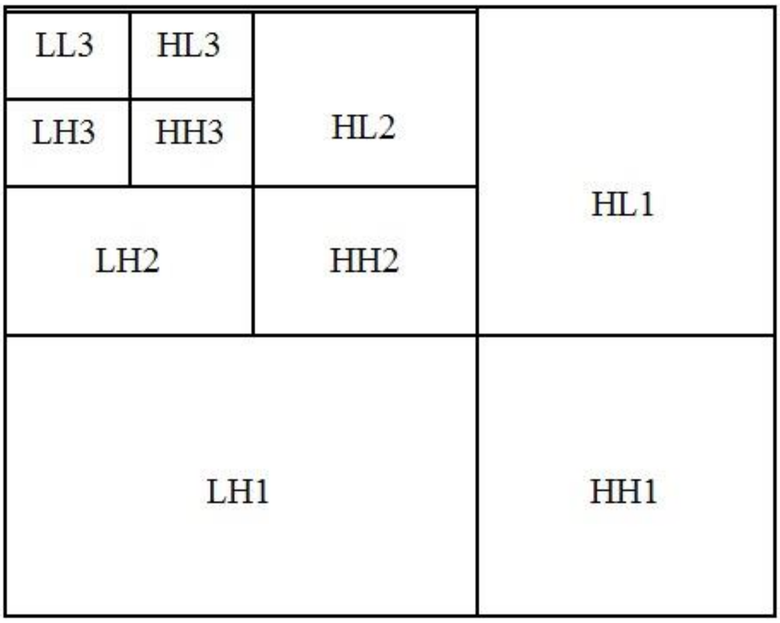

Fig 2: Three decomposition levels of Wavelet Coefficients structure

2. SCHEME DESIGN

Artificial neural network is important embranchment of artificial intelligence field, and it is widely parallel linked by a great deal of simply process units (neural unit), and it can simulate the structure core function of human brain neural system and has strong learning, generalization core nonlinear approximation capability. Neural network has certain advantage on the aspect of simulating biology neural computation [7], [8]. It has selflearning, selforganizing, association of ideas, blur extend abilities, etc. and has great comparability with human visual system. Neural network applied to digital watermark embedded process simulates human visual characteristic to determine the maximum watermark embedded intensity endured by middle frequency coefficients in every one of 8×8 image sub block DWT coefficients. In this paper, a computing method of the maximum watermark embedded intensity using FCNN is proposed in order to make watermark have good robustness against all kinds of attacks and embed the maximum watermark data under the condition of good invisibility.

A. Watermarking based on HVS model

Considering HVS aspects of the image to do watermarking is of high importance [6]. One of the important issues of HVS model is the image component masking. This issue is based on the fact that in a visual signal, a component remains invisible before the other signal. The second signal is called mask. In fact a signal strengthens the visual and perceptual thresholds for its other surrounding signals [1], [6]. The most common image masking components are as follows: frequency masking; entropy masking; texture masking; brightness masking; contrast masking [1]. The frequency masking describes the human's eyes sensitivity to the sine wave grating at various frequencies. This masking is also describable by contrast masking. The contrast masking states that the human's eye is less sensitive to make changes in high image frequencies. It is for the very reasons that in most of the watermarking methods the watermark is inserted in the image edges [3]. Brightness masking proves the effects of detectable noise thresholds on a constant background. Frequency masking is independent of the image and is based on the quantization table in the process of image compression. The other masking components are dependent on the image. Adaptive watermarking schemes use the HVS models that determine the image dependent upper bounds on watermark insertion (watermark payload) to gain maximum strength, transparent watermark insertion, which in turn is extremely robust to common image processing operations such as JPEG compression, rescaling, and cropping. The visual models provide thresholds (JND thresholds) for how much a given transform coefficient can change, before such changes are noticeable under standard viewing conditions. [4], [13].

B. Application of neural network in digital image watermarking

Neural network is used in watermarking algorithm in the processes of embedding and extracting watermark [5], [7], and [8]. Principally the watermark image size is less than the original image. The generic algorithm of watermark embedding is

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that the original images along with its watermark are applied into the neural network as input and target vectors (one dimensional vector) and neural network output is a one dimensional vector which is the watermarked image. In the process of watermark extracting, the watermarked images along with the original watermark are applied into the neural network and the neural network output is the extracted watermark which is one dimensional vector.

In this paper, we use the neural network to calculate the image JND threshold values. DWT coefficients are applied into the neural network as input vector and the JND threshold values, are calculated for each coefficient. In order to reach to more efficient watermarking algorithm, it is very important to avail the most suitable JND threshold values which are only possible through research, study, and practical implementation [6]. JND threshold values will be regarded as a target vector for neural network. The training set of the neural network is set of all block images that have the same masking feature. The output vector of neural network is maximum watermark embedded intensity values. Depending on our chosen coefficients for embed the watermark; corresponding values of output are used to embed the watermark. The process of calculating JND threshold values will be again done in the process of watermark extracting. Of course embedding and extracting algorithms have a close relation with each other and availing them requires practical implementation.

The purpose of this paper is to present a full counter propagation neural network for watermarking. The FCNN is designed to learn bidirectional mappings. Through the process of supervised training, the FCNN adaptively contrast a look up table approximating the mapping between the presented input/output training pair: X_s and Y_s. After being trained, the FCNN can be used to gain X^{s*} and Y^{s*}. Fig.3 shows the architecture of proposed FCNN [5].The sth one-dimensional X_s and Y_s be written in vector form as (1), and (2):

$$X^s = \{x_1^s, x_2^s, x_3^s, \ldots, x_i^s\} \qquad (1)$$

$$Y^s = \{y_1^s, y_2^s, y_3^s, \ldots, y_i^s\} \qquad (2)$$

Where i is a number of elements of the sth X, and Y. The input vectors X and Y are connected to neuron Z_i with weights W and U respectively as (3), and (4).

$$W = \{w_{11}, w_{12}, w_{13}, \ldots, w_{in}\} \qquad (3)$$

$$U = \{u_{11}, u_{12}, u_{13}, \ldots, u_{in}\} \qquad (4)$$

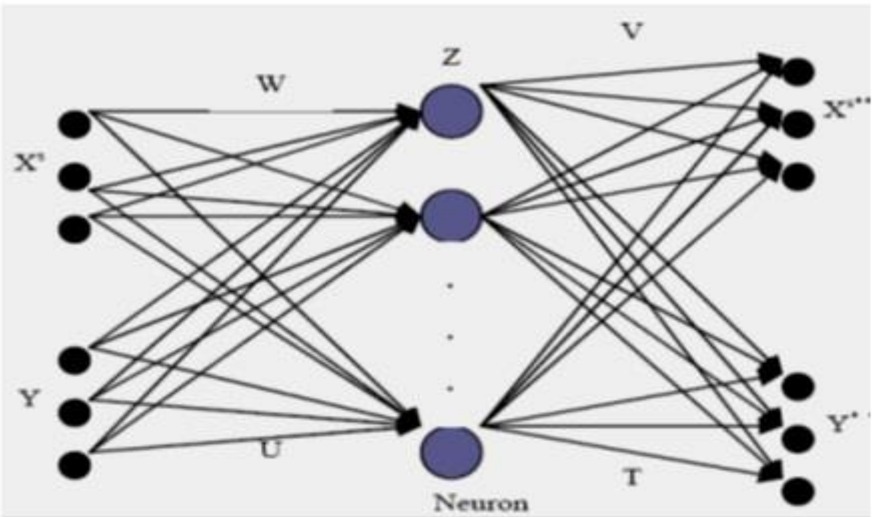

Fig 3: FCNN Architecture

Where w_{in} denotes the weight between ith neuron and input x_n. Similarly, u_{in} denotes the weight between ith neuron and input y_n. Accordingly, the total input of the ith neuron is Z_i, which represents the distance vector between input x_s, y_s pair and the ith neuron.

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$$Z_i = \sum_{i=1}^{n} (x_k^s - w_{ik})^2 + (y_k^s - u_{ik})^2 \qquad (5)$$

The activation function for each neuron is given by (6).

$$\Gamma_i = \begin{cases} 1 & \text{if } Z_i \text{ is the smallest for all i} \\ 0 & \text{otherwise} \end{cases} \qquad (6)$$

Therefore, the jth output of X^{s*} and Y^{s*} can be obtained by (7) and (8).

$$x_j^* = \sum_{i=1}^{n} \Gamma_i v_{ji} \qquad (7)$$

$$y_j^* = \sum_{i=1}^{n} \Gamma_i t_{ji} \qquad (8)$$

Where v_{ji} denotes the weight between ith neuron and output x^{js*}. Similarly, t_{ji} denotes the weight between ith neuron and output y^{js*}. The synaptic weights can be written in a vector form as (9), and (10):

$$V = \{v_{11}, v_{12}, v_{13}, \ldots, v_{ni}\} \qquad (9)$$

$$T = \{t_{11}, t_{12}, t_{13}, \ldots, t_{ni}\} \qquad (10)$$

Where n is the number of elements X_s and Y_s. The output errors of FCNN are calculated by (11) and (12).

$$Ec_j = | x_j^{s^*} - d_j |, j = 1 \ldots n \qquad (11)$$

$$En_i = | y_i - d_i |, i = 1 \ldots n \qquad (12)$$

Where d_i denotes the ith element value of first target vector n and d_j denotes the jth element value of second target vector. If output error is less than a predefined threshold, the network converges. The input weight vectors W and U are updated by (13), and (14).

$$w_{ij}(k+1) = [1 - a(k)] w_{ij}(k) + a(k) x_i^s \qquad (13)$$

$$u_{ij}(k+1) = [1 - a(k)] u_{ij}(k) + a(k) y_i^s \qquad (14)$$

Where a(k) is the learning rate of input layer. In addition, the learning rate a(k) is suitably decreasing function of learning time k. The learning function a(k) can be specified as follows:

$$a(k) = a(0) \exp(-\frac{k}{k_0}) \qquad (15)$$

Where a(0) is initial learning rates, k_0 is a positive constant. Similarly, the output weight vectors V and T associated with the winning neuron are updated by (16) and (17).

$$v_{ij}(k+1) = v_{ij}(k) + b(k) \mid x_i^s - v_{ij}(k) \mid \Gamma_i \qquad (16)$$

$$t_{ij}(k+1) = t_{ij}(k) + b(k) \mid y_i^s - t_{ij}(k) \mid \Gamma_i \qquad (17)$$

Where b(k) is the learning rate of output layer. It is calculated similar to a(k). After the FCNN converged, the output vectors obtained as (18), and (19).

$$X^{s*} = \{x_1^{s*}, x_2^{s*}, x_3^{s*}, \ldots, x_n^{s*}\} \qquad (18)$$

$$Y^{s*} = \{y_1^{s*}, y_2^{s*}, y_3^{s*}, \ldots, y_n^{s*}\} \qquad (19)$$

C. Watermark embedding process

In this paper we use 9/7 bi-orthogonal Discrete wavelet transform for watermarking. Instead of embedding the original watermark in the image, we embed an image-dependent watermark (IDW) in the original image. Then, using the original and image-dependent watermarks, we make a key matrix by which we can obtain the original watermark in the extraction process. IDW is a 64×64 matrix of the values 0 and 1 which are calculated regarding the special relations between the wavelet transform coefficients of each original image block. Original image is a 512×512 gray image which is divided into 8×8 sub blocks and got 64×64 image blocks which are shown as (20).

$$B(i, j), 0 \le i \le 63, 0 \le j \le 63 \qquad (20)$$

$B(i, j)$ is the block of image in (i,j) coordinates. Doing the Three decomposition level wavelet transform for each block, the image-dependent watermark is made according to following algorithm:

If $HL3(i, j) > LH3(i, j)$ *and* $HL3(i, j) > HH3(i, j)$ *and* $LH3(i, j) > HH3(i, j)$ *then* $IDW(i, j) = 1$ *else* $IDW(i, j) = 0$.

In this algorithm, $HL3(i, j), LH3(i, j), HH3(i, j)$ are the relevant three decomposition level wavelet transform coefficients for original image block $B(i, j)$. $IDW(i, j)$ is the entry of the ith row and jth column in the IDW matrix which is corresponding to the regarded block coordinates in the original image. Having calculated the values of IDW entries, the KEY matrix is calculated based on (21).

$$KEY = OW + IDW \qquad (21)$$

Where IDW is the image-dependent watermark matrix and OW is the original watermark, respectively.

JND threshold values are calculated considering the wavelet transform coefficients along with using FCNN technique. The structure of input, middle, and output layers of FCNN has two 9×9×9 nodes. The training set of FCNN are special wavelet coefficients transform of set of 8×8 adjacent blocks of original image, which make 64 one dimensional input vectors with size (9×1) for each input vector of FCNN at each training stage. If we do three decomposition levels wavelet transform for each 8×8 image block, there will be an 8×8 matrix of wavelet transform coefficients. From these 64 coefficients, we choose 9 including the coefficients of LL3, HL3, LH3, HH3, and the entries being in (1,3), (2,3), (3,1), (3,2), and (3,3) as set A, the coordinates which is arranged as (9×1) vector based on (22).

$$A = \{[LL3, HL3, LH3, HH3, C(1,3), C(2,3), C(3,1), C(3,2), C(3,3)]\} \qquad (22)$$

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The First target vectors for FCNN is JND thresholds which calculated based on the Luminance feature of mentioned training set image. The complete mathematic relations for calculating these JND thresholds are exist in [10]. The second target vector for FCNN is quantization value for wavelet coefficient of training set image which calculated in [11]. The target vectors regulated into (9×1) one dimensional vector. At first for FCNN, vectors V, U, V, and T set to arbitrary values. After finishing each training stage the mean value for each row entries of matrix W and U are calculated and considered as two (9×1) vectors, these two vectors merged as (23) .

$$FJND = \alpha.MW + \beta.MU \qquad (23)$$

In this relation MW and MU are the one dimensional vectors that their elements are equal the mean value for each row entries of matrix W and U respectively. The values of α and β have gotten experimentally, and comparing the implementation results. The merged vector consider as final JND (FJND) threshold values. The first element of this vector is FJND for LL3 coefficient that is used in watermark embedding and extracting process. At starting new training stage, training set is changed and the target vectors are calculated again for new training set. The calculated FJND is final JND threshold for input wavelet coefficients for all block images of the relevant training set. Each element of FJND vector is respectively final JND threshold for each element in input vector of the FCNN for all 64 vectors of the training set. The Process of calculating JND thresholds are shown in Fig.4.

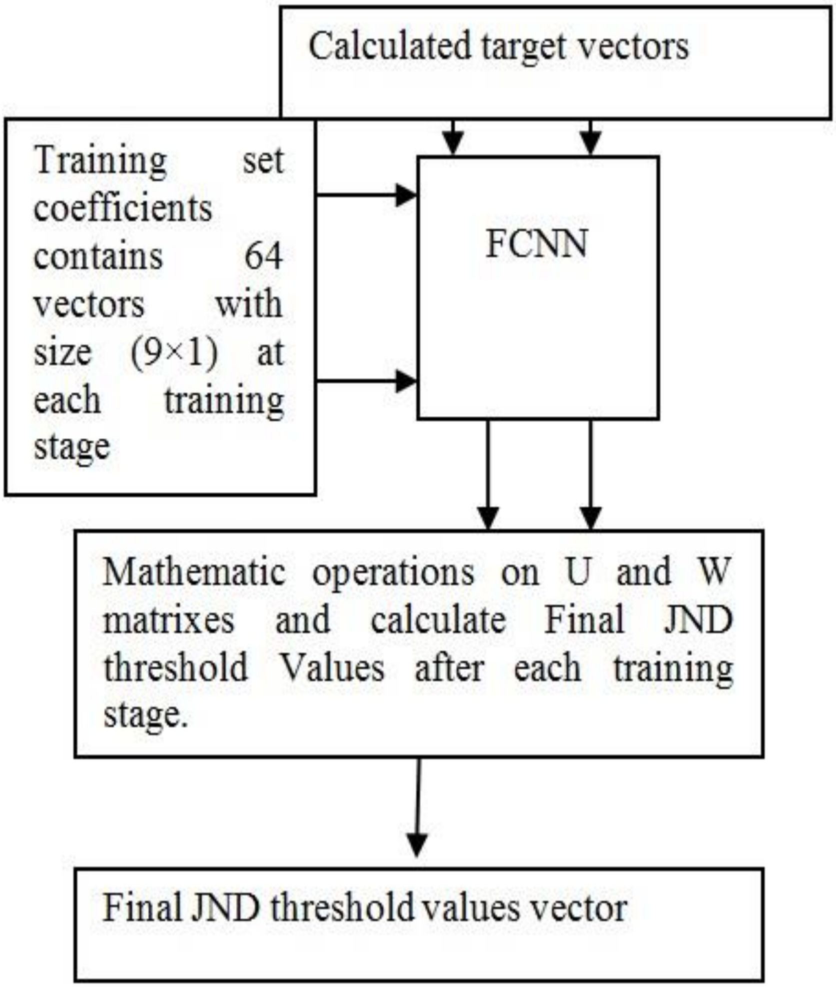

Fig 4: Calculating JND values by FCNN

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The original image is a 512×512 gray image which is divided into 8×8 blocks and so there will be 64×64 image block. In each image block, we embed one entry value of IDW matrix. For the set A that is mentioned in previous section, we define a neighboring mean value (NMV) for each coefficient of this set as (24).

$$NMV(x) = (\sum_{\forall C \in A} (C - x))/8, x \in A \qquad (24)$$

We calculate the NMV for LL3 coefficient [12]. The embedding algorithm will be as follows:

If $IDW(i,j)=1$ *then* *If* $NMV(LL3(i,j))>0$ *and* $LL3(i.j) > NMV(LL3(i.j))$ *then,* $LL3(i,j) = LL3(i,j) + FJND(LL3(i,j))$ *.Else* *if* $NMV(LL3(i,j))<0$ *and* $LL3(i.j) > NMV(LL3(i.j))$ *then* $LL3(i,j) = LL3(i,j) - FJND(LL3(i,j))$.

If $IDW(i,j)=0$ *then* *if* $NMV(LL3(i,j))>0$ *and* $LL3(i.j) > NMV(LL3(i.j))$ *then,* $LL3(i,j) = LL3(i,j) - FJND(LL3(i,j))$ *, Else if* $NMV(LL3(i,j))<0$ *and* $LL3(i.j) > NMV(LL3(i.j))$ *then,*

$LL3(i,j) = LL3(i,j) + FJND(LL3(i,j))$.

In above algorithm, $LL3(i,j)$ is the LL3 coefficient for block $B(i,j)$, $FJND(LL3(i,j))$ is the relevant final JND threshold for LL3 coefficient, and $NMV(LL3(i,j))$ is neighbouring mean value for LL3 coefficient, as discussed in previous section Having finished the algorithm of watermark embedding, Inverse wavelet transform is done for each coefficients block and the watermarked image will be obtained by putting the blocks together. This proposed embedding watermark scheme has been shown in Fig.5.

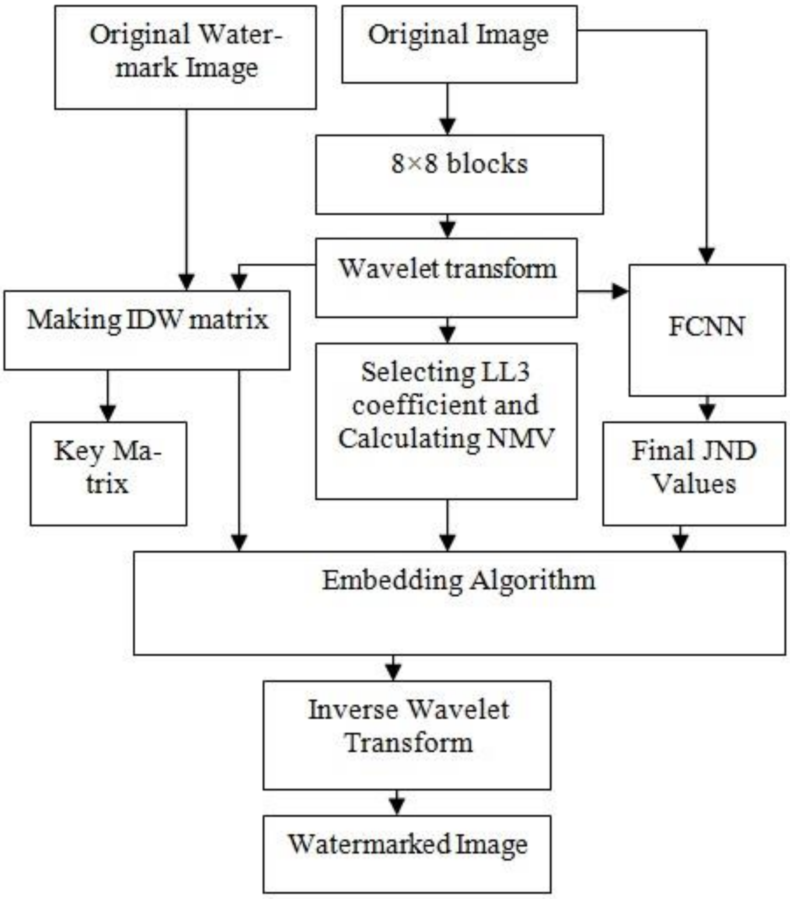

Fig 5.Embedding Process

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D. Watermark Extraction Process

In order to extract the watermark, we do three decomposition level wavelet transform for the watermarked image and the original image in a block by block manner and based on the embedding algorithm, we calculate the MNV for LL3 coefficient of each image coefficient block and extract the IDW matrix. This algorithm is as follows:

If $\frac{NMV(LL3_{WI}(i,j)) - NMV(LL3_{OI}(i,j))}{FJND(LL3(i,j))} > \frac{1}{2}$ *then* $IDW'(i,j) = 1$.

Else If $HL3(i,j) > LH3(i,j)$ *and* $HL3(i,j) > HH3(i,j)$ *and* $LH3(i,j) > HH3(i,j)$ *then* $IDW'(i,j) = 1$, *Else* $IDW'(i,j) = 0$.

In the above algorithm, $LL3_{WI}(i,j)$ is the LL3 wavelet transform coefficient related to watermarked image (WI) block $B(i,j)$, and $LL3_{OI}(i,j)$ is the LL3 wavelet transform coefficient related to original image (OI) block $B(i,j)$, $HL3(i,j), LH3(i,j), HH3(i,j)$ are the relevant three decomposition level wavelet transform coefficients for watermarked image block $B(i,j)$.

Having Extracted the IDW, we obtain the original watermark based on the (25).

$$OW' = KEY - IDW' \quad (25)$$

In this relation, KEY is the calculated key matrix in the making process of IDW, OW' is the original calculated watermark and IDW' is the image-dependant watermark extracted from the image. The proposed watermark extracting scheme has been shown in Fig 6.

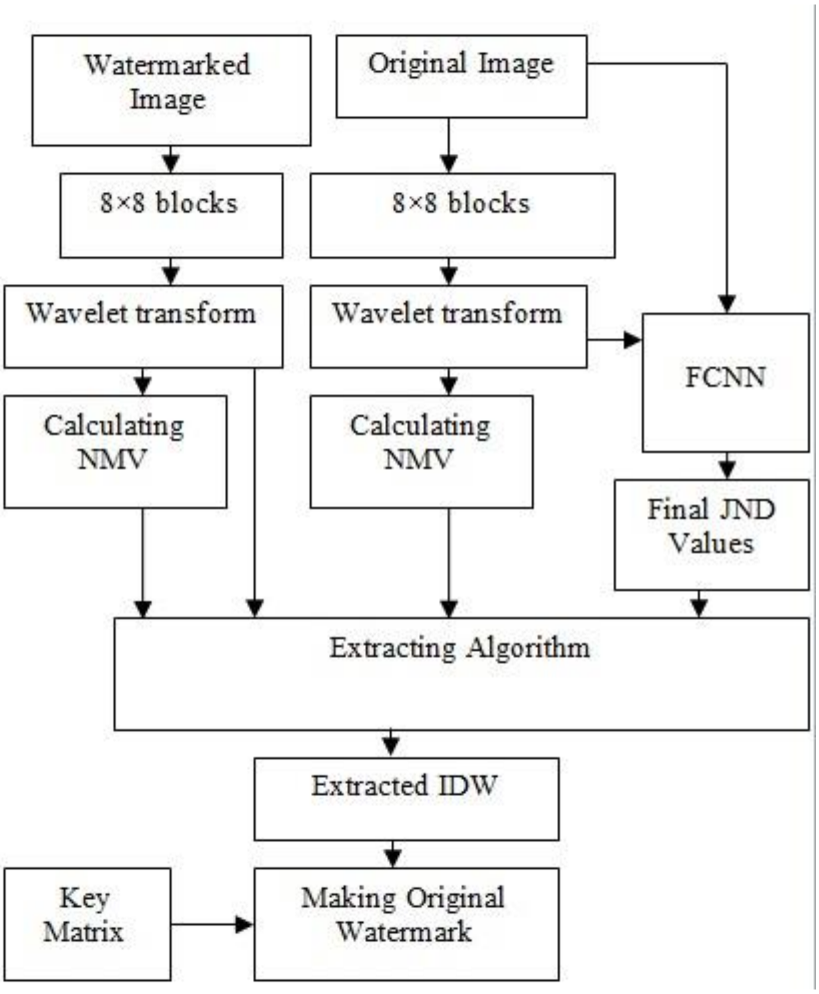

Fig 6.Extracting Process

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3. IMPLEMENTATION RESULTS

The original and the watermarked images have been shown in Fig.7-10. Barbara and Cameraman image have been used to implement the watermarking algorithm. Original Watermark is a binary image and its size is 64 × 64. The original watermark image is shown in Fig.11. The value of coefficients α, β in JND calculating process has been set sequentially to .7, and .3. By these values, the maximum performance for watermarking algorithm has been obtained. The performed attacks on the watermarked image are as follows: Gaussian noise; median filtering; low pass filtering; cropping and resizing the image; jpeg compression with quality factors of 10, 25, 50, 75, and 90 and finally jpeg 2000 compression. The estimate of similarity between the extracted watermark image and the original watermark image according to (26), along the peak signal to noise ratio (PSNR) of watermarked image based on (27), will be calculated having performed each one of the mentioned attacks on the watermarked images, and results have been integrated in table (1,2). In (26) J is the original watermark and J' is the Extracted original watermarked from extracting watermark algorithm. Dot operation in this relation is explanatory sum of product of respective entries between matrix J, J', and square operation is explanatory sum of product of each entry of matrix J with itself.

$$sim(J,J') = \frac{J.J'}{J^2} \times 100 \qquad (26)$$

$$PSNR = 10\lg\left(\frac{255}{\sum_{i,j}(OI(i,j) - WI(i,j))}\right)^2 \qquad (27)$$

Fig 7: Original Barbara Image

Fig 8: Watermarked Barbara Image

Fig 9: Original Cameraman Image

Fig 11: Watermark image

Fig 10: Watermarked Cameraman Image

4. CONCLUSION

A robust and efficient watermarking method of digital images based on wavelet transform and FCNN was presented in this paper. The watermarking algorithm used an intelligent neural network to simulate the HVS model of the image. The HVS model of image is in conformity with the image luminance and quantization value based on relation between wavelet coefficients and image-dependent watermark. Our watermarking algorithm embeds the watermark in the image imperceptibly and invisibly, so that this process doesn't damage the quality, brightness, clearness, and the other image HVS characteristics. The implementation results show that this watermarking algorithm has very good robustness to all kind of attacks.

Table.1. Implementation Results and Comparisons for Barbara Image

Kinds of Attack on Barbara image	Proposed Method		Method in [14]		Method in [15]	
	PSNR	SIM	PSNR	SIM	PSNR	SIM
Gaussian Noise	24.3	79.1	27	98.3	31.3	92.3
Low Pass Filter	29.8	91.8	25.8	92.8	29	88.8
Median Pass Filter	31.6	92.6	27.4	95.7	34.7	97.6
Scaling 1/5	16.9	73.4	20.0	86.3	17.5	81.0
Jpeg 75%	**40.1**	**99.6**	**37.4**	**98.9**	**39**	**97.5**
Jpeg 25%	**38.0**	**96.0**	**34.7**	**94.5**	**36.9**	**93.8**
Jpeg 10%	**33.5**	**94.3**	**28.2**	**91.2**	**32.6**	**89.9**
Jpeg 2000 with bitrate 3	18.7	74.5	19.4	88.1	25.1	88.7

Table.2. Implementation Results and Comparisons for Cameraman Image

Kinds of Attack on Cameraman image	Proposed Method		Method in [15]		Method in [16]	
	PSNR	SIM	PSNR	SIM	PSNR	SIM
Gaussian Noise	25.8	80.6	31.5	93.7	32.15	94.4
Low Pass Filter	27.5	87.3	30	89.5	31	92.5
Median Pass Filter	30.2	90.1	36.2	94.2	30.0	88.1
Scaling 1/5	14.2	71.5	26.8	82.1	27.3	84.5
Jpeg 75%	**39.5**	**97.5**	**39.3**	**97.7**	-	-
Jpeg 25%	**34.9**	**94.2**	**36.4**	**92.2**	**33.0**	**90.0**
Jpeg 10%	**31.1**	**91.0**	**35.4**	**90**	**24.2**	**87.2**
Jpeg 2000 with bitrate 3	19.2	75.4	29.0	87.1	22.0	83.0

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