Fuzzy Neural Based Copyright Protection Scheme for Superresolution

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Abstract: Superresolution is an algorithmic approach, for constructing high resolution de-noised image from its low resolution and noisier version. A new method to address the problem of copyright violation for super resolution is presented in this paper. The goal is to design an improved watermarking technique, while minimizing distortion in the super resolved image. The approach employs, fuzzy logic to build the perceptual mask, embeds watermark in the low frequency coefficients for robustness with edge preservation and use neural network at the receiver. Novelty lies in providing copyright protection jointly to the low resolution and the super resolved images. The distortion due to watermark insertion is compensated by: 1. use of fuzzy perceptual mask tuned to human visual system; 2. use of trained neural network estimator during watermark extraction; 3. utilize image degradation model during watermark extraction. Effectiveness of the proposed approach is shown by conducting the experiments on natural images and comparing it with the state of the art techniques.

Index terms: Fuzzy inference system, neural network, super resolution, watermark

I. INTRODUCTION

Super-Resolution (SR) refers to an algorithmic approach to construct high resolution (HR) images, from single or multiple low resolution (LR) images. SR is classified into two classes; reconstruction based; and learning based. In the reconstruction based approach, multiple LR images of the same scene, are captured by the camera and the additional information available in each of these images is used for constructing SR image [1]. However, in many applications, multiple observations may not be available. In such case, high-resolution image is generated with just a single LR image [2], [3], [11]. In the learning based approach [4], for a given single LR observation, a training database is used to learn the details or any suitable characteristics, to obtain the corresponding SR image. These algorithms, use a learning scheme to capture the high-frequency details by determining the correspondence between LR and HR training images. Compared to traditional methods, which basically process images at the signal level, learning based SR algorithms incorporate application dependent priors to infer the unknown high resolution image [5].

SR find applications in the domain of medical imaging, remote sensing [6], biometrics, image fusion [7], image inpainting [8], etc.. Many of these application areas, require copyright protection due to data sensitivity and commercial interests. A variety of image watermarking techniques have been proposed in the literature [12] - [13]. Some of these techniques are based on discrete wavelet transform (DWT) [14] [15] and contourlet transform[16]. Watermarking tries to achieve optima between contrasting requirements of robustness, perceptual fidelity and capacity [14] - [15], therefore, it can be seen as an optimization problem.

Improvement in the robustness due to watermark embedding directly into a super resolved image has been reported in [9]. SR image is generated from the sparse representation of an image and the K-SVD (singular value decomposition) algorithm [10]. However, this method suffers from several disadvantages if applied explicitly for copyright protection of the SR. The disadvantages are: 1. SR and watermark elements of the algorithm are completely isolated and watermark is embedded directly into the SR image. For a holistic solution, these parts have to be interdependent; 2. improvement in robustness is not the characteristics of the watermarking technique, but it is due to watermark embedding in higher signal to noise ratio (SNR) signal i.e. SR.; 3. the method does not elaborate on actual fidelity loss in the SR image and reduction in SNR due to insertion of the watermark; 4. method discusses resistivity against very limited set of attacks like joint photographic expert group (JPEG) compression and noise addition; 5. quantitative discussions about the usage of error correcting codes are completely missing. From the literature survey [12] - [19], it can be concluded that no work has been reported explicitly on the copyright protection of the SR.

Deployment of the large number of mobile devices has opened new application vistas where SR is valuable. One such application is, digitally recreating past grandeur of the historical monuments and relaying it to the mobile devices of a willing tourist at a cost. The key feature of mobile application is, zooming on to region of interest and storing it. This requires implementation of a SR algorithm. At the same time, to prevent tourist from commercially misusing captured SR images, requires execution of the copyright protection mechanism on the SR image. This motivates us, in this work, to integrate copy right protection mechanism directly into the SR realm.

The main contributions of the proposed paper to overcome limitations of [9] and to develop efficient copyright protection in SR include: 1. the watermarking scheme, that provides protection to both the LR and the SR; 2. design a seamless
technique interconnecting SR and watermarking; 3. the method compensate, reduction in the SNR arising out of watermark insertion by using a) fuzzy perceptual mask b) trained back propagation neural network (NN) at the receiver c) use image degradation model to estimate decimating coefficients for down sampling SR image to LR at the receiver; 4. low frequency, watermark insertion preserves edge integrity and maintain perceptual fidelity of a SR image.

The rest of the paper is organized as follows. Section II, discusses the development of fuzzy perceptual mask for watermarking. Use of a neural network for learning unwatermarked coefficients is discussed in section III. Decimation coefficients estimation is covered in section IV. Watermarking algorithms are covered in section V whereas section VI shows results of the proposed approach. Conclusions are drawn in section VII.

II. DEVELOPMENT OF FUZZY PERCEPTUAL MASK FOR WATERMARKING

Masking of frequency domain coefficients, for exploiting psycho visual effects of the human visual system (HVS), is commonly used in many compression standards like; JPEG or JPEG 2000. Masking enhances perceptual fidelity of the image, with increased compression ratio. Many models, exploiting limited dynamic range of the HVS, exists in the spatial and the frequency domain. In one such approach authors [17], developed a wavelet based fuzzy perceptual mask for images. They used a fuzzy logic, to build a non linear HVS model for perceptual mask in DWT. For each wavelet coefficient in a sub band, a single mask value based on brightness, edge, and texture is computed. They showcased the application for a non blind watermarking scheme and compression. In another attempt authors [18] fused fuzzy logic with contourlet transform to build the watermarking system. They used fuzzy logic to obtain optimal parameters for the contourlet transform from user’s perspective. Authors defined fuzzy sets in terms of capacity, fidelity, and robustness of the watermarking application and used quantization based data hiding technique. Authors in [19] utilized the Watson [20] visual model to embed the watermark in DCT and DWT coefficients. The visual model defines a Just Noticeable Difference (JND) mask by using texture and luminance of the image. Universal entropy based masking model for watermarking is proposed in [21]. The JND values are computed based on perceptual and entropy masking.

Based on multi resolution theory each of the approximate band coefficient is related to finer horizontal, vertical and diagonal band coefficients. In the proposed method, fuzzy mask is computed using the Mamdani inference system for the approximate band by using information available from the finer band. Approximate band is used to insert the watermark. Fuzzy mask is generated as follows. 1. Gray scale LR image is decomposed up to three levels using Haar wavelet. 2. Fuzzy perceptual mask is generated by fusing texture, frequency of the LH3 (horizontal details), HL3 (vertical details) and HH3 (diagonal details) sub bands along with luminance component of the LL3 band (approximation details). LH3, HL3, and HH3 bands provide signal’s high frequency information with LL3 giving more precise low frequency information. The mask has same size as the LL3 band. Thus weighing factor for each LL3 band coefficient is computed at the output of fuzzy inference system (FIS). Block diagram of FIS is shown in figure 1.

The texture is considered as a standard deviation over 3 x 3 neighborhoods for LH3, HL3, and HH3 bands. The luminance component is based on the coefficients of the approximate LL3 subband. The frequencies present in LH3, HL3 and HH3 are third input to the fuzzy inference system. All the input variables are fuzzified using the bell shaped membership functions into three fuzzy sets of “low”, “medium” and “high”. Similarly output fuzzy variable weights is also divided into three fuzzy sets of “low”, “medium” and “high” using bell shaped membership functions. The fuzzy rules are based on the following facts about the HVS: 1. eyes are less sensitive to changes in the areas of high brightness; 2. eyes cannot perceive changes in the areas with high texture; 3. eyes are less sensitive to changes in the high frequency bands. Based on the above facts some of the exemplary rules are as follows: 1. If brightness is HIGH texture is HIGH frequency is HIGH, then weight is HIGH. 2. If brightness is LOW texture is LOW frequency is LOW, then weight is LOW. 3. If brightness is LOW texture is MEDIUM frequency is MEDIUM, then weight is MEDIUM.

The output of each rule is aggregated into a fuzzy set. The crisp value for the weighing factor is obtained after defuzzifying the fuzzy set.

III. NEURAL NETWORK ESTIMATOR FOR LEARNING UNWATERMARKED LL BAND COEFFICIENTS

Problem of finding a mathematical model given input – output data pair is known as system identification or system modeling [22]. This is specifically of interest, in case nonlinear mapping between input and output, exists. Multilayer back propagation NN has proven to be a good means for nonlinear system identification. This property of the NN is exploited in the present work. As per the information theoretic model of watermarking proposed by P. Moulin [24], original unwatermarked signal can be regarded as the side information. This information can be used to improve detection of the watermark. However, usage of original signal for detection is undesirable due to security issues. Therefore, watermarking detector in the proposed work use trained neural network to estimate un-watermarked LL3 band coefficients given watermarked LL3 band coefficients at the input. NN regenerates the side information at the receiver without original image at the receiver. For this purpose, a two layered back propagation NN is used as depicted in figure 2.
The watermarked LL1 band coefficients and un-watermarked LL3 band coefficients form input – target pairs for the NN. The training of NN is an online offline process. The input and output layer of NN has 64 neurons with the hidden layer containing 256 neurons. Neural network is trained on 10 different images simultaneously with 50% of input – output pairs used for training, 25% of pair for testing, and 25% for validation. Validation pairs helps in estimating the over fitment of the function. Scaled conjugate gradient [23] algorithm is used for learning due to high data dimensionality. Testing data in the form of LL3 band watermarked coefficients is used at the watermarking receiver.

IV. ESTIMATION OF DEGRADATION COEFFICIENTS

At the receiver down sampled version of SR is used for extraction of the watermark. Decimation coefficients are estimated from the watermarked pair of LR and SR. The process of estimation is discussed as follows. In a SR problem, the forward model for image formation is formulated as \( y = Az + n \), where \( y \) is the watermarked LR and \( z \) is a watermarked SR. \( y \) and \( z \) represents lexicographically ordered vectors of size \( M^2 \times 1 \) and \( q\times M^2 \times 1 \) respectively. \( A \) is the degradation matrix that represents blurring and down sampling. \( n \) is the independent and identically distributed (i.i.d.) noise vector with zero mean and variance and has same size as \( y \). In the literature, degradation model used to obtain the aliased pixel intensities from the high resolution pixels has the form [25].

\[
A = \frac{1}{q^2} \begin{pmatrix}
1 & 1 & \ldots & 0 & 0 \\
0 & 1 & \ldots & 1 & 0 \\
0 & 0 & \ldots & 1 & 1 \\
\end{pmatrix}
\]  

(1)

In equation (1), the degradation matrix indicates that a low resolution pixel intensity \( y(i, j) \) is obtained by averaging the intensities of \( q^2 \) pixels corresponding to the same scene in the high resolution image and adding noise intensity \( n(i, j) \). This assumes that the entire area of a pixel acts as the light sensing area and there is no space in the pixel area for wiring or insulation. However, in practice, the observed intensity at a pixel captured due to low resolution sampling depends on various factors, such as; blur, aliasing, camera gain, illumination condition, zoom factor, noise etc. Thus, there could be unequally weighted sum of high resolution intensities while obtaining the degraded image. However, these weights are unknown and needs to be estimated. Watermarked SR and the watermarked LR test image is used to obtain the weights. The degradation matrix can now be obtained as

\[
A = \frac{1}{q^2} \begin{pmatrix}
a_1 & a_2 & \ldots & a_{q^2} & 0 & 0 \\
0 & a_1 & a_2 & \ldots & a_{q^2} & 0 \\
0 & 0 & a_1 & a_2 & \ldots & a_{q^2} \\
\end{pmatrix}
\]  

(2)

where, \( |a_i| < 1, i = 1, 2, \ldots, q^2 \) represents the weights to be estimated. Using these weights one can write the degraded pixel intensity at a location \( (i, j) \) for a zoom factor of \( q = 2 \) as, \( y(i, j) = a_1 z(2i, 2j) + a_2 z(2i, 2j + 1) + a_4 z(2i + 1, 2j) + \ldots + a_{q^2} z(2i + 1, 2j + 1) + n(i, j) \)

One can estimate \( a_i 's \), where, \( i = 1, 2, \ldots, q^2 \) by minimizing \( \| y - Az \| \). In order to ensure that \( a_i \geq 0 \), one can use non negative constrained least square (NNLS) [26]. This makes estimated \( a_i \) more accurate and close to the true value. Even though \( a_i \) are estimated at the watermarking embedder, they are used at the receiver.

V. WATERMARKING ALGORITHMS

Watermark embedding algorithm flow is shown in figure 3. The steps are enumerated as follows:

1. Decompose LR image \( I_{LR} \) to third level using Haar wavelet.
2. Compute fuzzy mask \( M \) for all LL3 band coefficients \( c_{LL} \) as discussed in section II.
3. Modulate LL3 band coefficients with watermark \( W \) as \( C_{nLL}^3(i, j) = C_{LL}^3(i, j) + M(i, j) \times W(i, j), \n, \forall (i, j) \)

where, \( C_{nLL}^3(i, j) \) is modified LL3 coefficients at the location \( (i, j) \).
4. Reconstruct watermarked LR image \( I_{LR} ^W \) by applying inverse Haar wavelet.
5. Super resolve \( I_{LR} ^W \) by a factor 2x to obtain SR image \( I_{SR} ^W \).

Available SR algorithms [27] are used for generating \( I_{SR} ^W \).

Figure 3. Watermark embedding

The steps for watermark extraction shown in figure 4 are outlined as follows:

1. Received noisy watermarked SR image \( I_{SR} ^W \) is down sampled by 2x to form noisy watermarked LR image \( I_{LR} ^W \). The image is decimated by using the degradation matrix as obtained in section IV. The four decimation coefficients \( a_i 's \) are shared with the extraction stage. These \( a_i 's \) also act as the secret key.
2. Decompose \( I_{LR} ^W \) to three levels using Haar wavelet.
3. Re-compute the fuzzy mask \( M' \) for each noisy LL3 band coefficient \( C_{nLL}^3 \) using third level finer bands and low frequency band as discussed in section II.
4. \( C_{nLL}^3 \) is given as an input of the trained NN, whose output is an estimated un-watermarked LL3 band
coefficients $C_{LLH}$. The neural use for system identification is outlined in section III.
5. Finally, the watermark is extracted as follows:

$$\hat{W}(i,j) = \frac{C_{LLH}(i,j)-C_{LLH}(i,j)}{W(i,j)} \quad \forall i,j.$$

(4)

The $\hat{W} \equiv W$ proves copyright and ownership.

VI. RESULTS AND DISCUSSIONS

The images used for experimentation are derived from the heterogeneous set [30]. LR gray scale images of size 256 x 256 were super resolved by 2x to the size 512 x 512. Also, test images are available in their native resolution of 512 x 512 to provide the ground truth for comparison. Visual binary watermark of size 64 x 64 is used during the experimentation. The estimated $a_t \in \{0.2753, 0.2239, 0.2225, 0.2819\}$. Some of the watermarked images are shown in figure 5. Watermarked image perceptual fidelity is measured by the peak signal to noise ratio (PSNR) calculated between image and its watermarked version. The number below each image indicates its PSNR value in dB.

![Figure 4 Watermark extraction](image)

![Figure 5 Various watermarked images](image)

Watermarking is a quest to find an optimal solution between robustness, capacity, and perceptual fidelity. In order to evaluate performance of the proposed scheme these three parameters are used. Robustness is quantified in terms of normalized correlation of the recovered watermark; capacity in terms of number of watermarking bits embedded and perceptual fidelity quantified in terms of the PSNR of a watermarked image. Proposed scheme is compared with several state of the art approaches using fuzzy and non fuzzy perceptual mask. Results of the perceptual fidelity and capacity are indicated in Table I and II. Performance numbers indicated in Table I and II are quoted from the respective papers for similar size images and watermark. Even though PSNR for [19] is marginally better than the proposed approach in few cases, it should be noted that capacity of the proposed approach is four times more than [19].

<table>
<thead>
<tr>
<th>Image</th>
<th>[17]</th>
<th>[28]</th>
<th>[19]</th>
<th>[21]</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lena</td>
<td>40.52</td>
<td>35.76</td>
<td>43.80</td>
<td>42.41</td>
<td>45.55</td>
</tr>
<tr>
<td>Pepper</td>
<td>41.64</td>
<td>37.54</td>
<td>43.94</td>
<td>--</td>
<td>43.07</td>
</tr>
<tr>
<td>Plane</td>
<td>40.73</td>
<td>35.87</td>
<td>41.93</td>
<td>--</td>
<td>41.79</td>
</tr>
</tbody>
</table>

Table II. Capacity in bits per pixel (bpp) for watermark

<table>
<thead>
<tr>
<th>Capacity</th>
<th>[17]</th>
<th>[28]</th>
<th>[19]</th>
<th>[21]</th>
<th>[9]</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.003</td>
<td>0.003</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.062</td>
</tr>
</tbody>
</table>

Proposed scheme is tested for robustness against various distortions. Robustness is enumerated in terms of normalized correlation (NC) between recovered $\hat{W}$ and embedded watermark $W$. The value of NC close to 1 indicates high resistivity of watermark against various attacks. Table III show NC against various image processing manipulations. Values of NC’s are quoted from respective papers to provide comparative metric with proposed method. Similarity in attacks, and images for all methods is ensured for fair comparison.

<table>
<thead>
<tr>
<th>Attacks</th>
<th>[17]</th>
<th>[19]</th>
<th>[29]</th>
<th>[9]</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>JPEG (50%)</td>
<td>0.83</td>
<td>0.76</td>
<td>---</td>
<td>0.95</td>
<td>0.99</td>
</tr>
<tr>
<td>Gaussian noise $(\mu=0, \sigma^2=0.001)$</td>
<td>0.91</td>
<td>0.80</td>
<td>0.86</td>
<td>---</td>
<td>0.86</td>
</tr>
<tr>
<td>Low pass filter 3 x 3</td>
<td>---</td>
<td>0.72</td>
<td>0.70</td>
<td>---</td>
<td>0.9</td>
</tr>
<tr>
<td>Salt and pepper noise 1%</td>
<td>---</td>
<td>0.88</td>
<td>0.99</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td>Noise density</td>
<td>---</td>
<td>0.67</td>
<td>0.99</td>
<td>0.95</td>
<td>0.95</td>
</tr>
<tr>
<td>Salt and pepper 3%</td>
<td>0.822</td>
<td>0.8489</td>
<td>---</td>
<td>---</td>
<td>0.98</td>
</tr>
<tr>
<td>Noise density</td>
<td>0.783</td>
<td>0.98</td>
<td>---</td>
<td>---</td>
<td>0.99</td>
</tr>
<tr>
<td>Rotation 45$^\circ$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.98</td>
</tr>
<tr>
<td>Cropping</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.99</td>
</tr>
</tbody>
</table>

Proposed method prevents extensive degradation in the SR image’s PSNR value due to the watermark insertion. This is validated by calculating PSNR (dB) between ground truth high resolution (HR) images and the watermarked / unwatermarked versions of SR. The results of experimentation are shown in Table IV.

<table>
<thead>
<tr>
<th>Image</th>
<th>PSNR without watermarked SR</th>
<th>PSNR with watermarked SR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cameraman</td>
<td>27.62</td>
<td>27.51</td>
</tr>
<tr>
<td>Lena</td>
<td>28.21</td>
<td>27.09</td>
</tr>
<tr>
<td>Baby</td>
<td>32.53</td>
<td>32.41</td>
</tr>
<tr>
<td>Classroom</td>
<td>26.29</td>
<td>26.26</td>
</tr>
<tr>
<td>Boy</td>
<td>24.40</td>
<td>24.38</td>
</tr>
<tr>
<td>Nature</td>
<td>24.52</td>
<td>24.50</td>
</tr>
</tbody>
</table>

VII. CONCLUSIONS

In this paper, a robust watermarking scheme for superresolution has been presented. By inserting watermark in LR, a seamless dependency between SR and watermarking is
established. Use of fuzzy mask, degradation coefficients, and tuned neural network has minimized degradation in PSNR of the SR image as indicated in Table IV. Usage of fuzzy perceptual mask has improved fidelity of the watermarked LR images with better capacity as compared to all other methods. This fact is reflected in Table I and II. Use of neural network in estimating un-watermarked DWT coefficients method results in informed watermark detection. Thus method exhibits higher robustness against many attacks. Proposed method has shown improvement in all three dimensions of watermarking viz. perceptual fidelity, capacity and robustness and it out performs other peer approaches.

References

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[27] Available online at http://lcav.epfl.ch/software/superresolution