Markov Random Field based Image Restoration with aid of Local and Global Features

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ABSTRACT
Image restoration is the process of renovating a corrupted/noisy image for obtaining a clean original image. Numerous MRF based restoration methods were utilized for performing image restoration process. In such works, there is a lack of analysis in selecting the top similar local patches and Gaussian noise images. Hence, in this paper, a heuristic image restoration technique is proposed to obtain the noise free images. The proposed heuristic image restoration technique is composed of two steps: core processing and post processing. In core processing, the local and global features of each pixel values of the noisy image are extracted and restored the noise free pixel value by exploiting the extracted features and Markov Random Field (MRF). Moreover, the restored image quality and boundary edges are sharpened by the post processing function. The implementation result shows the effectiveness of proposed heuristic technique in restoring the noisy images. The performance of the image restoration technique is evaluated by comparing its result with the existing image restoration technique. The comparison result shows a high-quality restoration ratio for the noisy images than the existing restoration ratio, in terms of peak signal-to-noise ratio (PSNR).

Keywords
Image Restoration, Markov Random Field (MRF), Feature Extraction, Random Noise, PSNR

1. INTRODUCTION
Now-a-days, the image processing techniques has made an immense contribution in all aspects of tech-savvy society [2]. Usually, images are produced to record or to expose some precious information incorporated in them. In image processing technique, Image Compression, Image Enhancement, Image Restoration, and Measurement Extraction are mainly important processes [5] [14]. The recorded image constantly represents a stained version of the original scene, due to blemishes in the imaging and capturing process, [4]. Mainly, images are spoiled due to the incidence of noise, scanned old photo paper, dust or blots lying on the scanning glass of a scanner, scratched images or others have labels or stamps [1].

In many applications, digital image restoration techniques have recently drawn much attention like super-resolution, digital auto-focusing, and more [3]. The process that makes an attempt to rebuild or recover a tarnished image by using derivable knowledge of the degradation phenomenon is known as image restoration. Thus, to retrieve the original image, the restoration techniques used in images are oriented towards modeling the degradation and applying the inverse process [15]. Different factors such as atmospheric disorder, relative motion between an object and the camera, an out-of-focus camera, or variations in electronic imaging components, may damage the images [9]. To improve the quality of a stained image is the main function of restoration techniques [6]. Image restoration technique is largely used in a number of applications, namely medical imaging, astronomical imaging, remote sensing, microscopy imaging, photography deblurring, forensic science and more [12].

There are two varied categories under which one can categorize image restoration and they are Spatial Domain and Frequency Domain [7]. With several capable algorithms, image restoration is one of the accepted fields of research [20]. Generally, in some transform domains, images have different sparse representations (or sparse approximations). Such transforms can be Fourier or windowed Fourier transforms, local cosine transforms, wavelet or framelet transforms, or discrete gradient operators [8]. The different processes carried out for recovering the original images are Inverse Filter, Weiner Filtering, Wavelet Restoration, and Blind Deconvolution [19]. When the noise is additive and Gaussian, among the classes of all filtering operations, linear filtering is most favorable [10]. In the last two decades, Tychonoff Regularization is one of the eminent techniques employed. Additionally, the topological optimization has drained the attention of a number of researchers in the recent past [13].

In imaging, image restoration or reconstruction is one of the initial and most traditional linear inverse problems [16]. To estimate an image from signals physically or mathematically associated to it is known as the image revival problem [11]. The restoration of unclear and noisy images is an ill-posed inverse problem [18]. Linear inverse problems occur in a number of applications like astrophysics, signal and image processing, statistical inference, optics and more [17].

Restoration is essentially used to develop the quality of a digital image that was tarnished due to a variety of phenomena like Motion, an improper focusing of camera during acquisition of image, Atmospheric turbulence, and Noise. Few image restoration methods are available that are in brief discussed in the following section 2. Different mechanisms are utilized in existing researches and such methods are not aware of Markov Random Field (MRF), which is one of the most efficient methods for the image restoration. On the basis of MRF method, only very few researches are obtainable in image restoration. When the image noise is Gaussian, the performance level of restoration is corrupted in such works. However, high PSNR restored images are not provided by such technique. Therefore, it degrades the image restoration accuracy.

In this work, a heuristic image restoration technique with the aid of modified NLR_MRF (MNLR-MRF) is proposed. The proposed image restoration technique reduces the drawback of existing image restoration method by determining the local and global features. The features computation process increases the correlation between the pixels in the input image. The features of the pixel values are utilized to replace the noisy pixel values with the restored pixel values through the Markov Random Field (MRF). MRF restores the noisy image pixel values with the help of local and global features. The restored image boundaries are improved by the post processing boundary sharpening method. The rest of the paper is organized as follows: Section 2 reviews the related works with respect to the proposed method. Section 3 presents the proposed heuristic technique, which is detailed in its subsections. Section 4 discusses about the implementation results, and Section 5 concludes the paper.

2. RELATED WORK

Only few number of research works are available in the literature that deals about the image restoration. A few of the most modern literature works in this topic are reviewed in this section.

Mairal et al. [21] have addressed the difficulty of learning dictionaries for different color image. The work has extended the K-SVD based grayscale image denoising algorithm. Their research has provided the behavior for managing different noise and missing information. It has also produced acceptable results in different applications such as color image denoising, demosaicing, and inpainting.

Babacan et al. [22] have proposed an algorithm by variational distribution approximations, for parameter assessment in total variation (TV) based image restoration. The restored image and the anonymous hyper-parameters for the image prior and the noise have been predicted parallel within the hierarchical Bayesian formulation. To the posterior distributions of the latent variables by means of variational techniques, the proposed algorithm has provided approximations. Additionally, some of the modern approaches in TV-based image restoration were exceptional cases of their framework. Without any assumptions about anonymous hyper-parameters, experimental results have proved that the proposed approaches have provided competitive performance and performed better than the existing techniques when extra information is incorporated.

Digital Inpainting refers to the elimination of different image defects such as scratches and blotches as well as removal of disturbing objects as for instance, subtitles, logos, dates etc. It restores the similar with information surrounding them which it merges faultlessly with rest of the image. Goyal [23] has proposed a digital image inpainting algorithm. This algorithm is provoked by the quality of results, easier implementation, efficiency, and effectiveness. After using this algorithm, the restored images obtained were seemed to be obvious and surprisingly greater in some cases. Also, in terms of working out time and image quality while filling-in large region, it has edge over other algorithms.

Sun et al. [24] have introduced a gradient-based discriminative learning technique to study the possible functions and non-local range filter bank. While the gradients of loss function with respect to model parameters were clearly calculated, to train the proposed model robust gradient-based optimization techniques have been in use. They have implemented this framework for eliminating noise from the image as well as from inpainting. Results have shown that the learned NLR-MRF model has considerably performed well than the predictable MRF models and created satisfactory results.

Rabbani [25] has developed a spatially adaptive wavelet-based image denoising algorithm for various low signal-to-noise ratio (SNR) magnetic resonance (MR) images. This has compared the results with other techniques. To improve the visual quality of noisy MR images with very low computational cost, simulation results have proved that the proposed algorithm has the potential. In case the input MR image is vague, for visual quality development, a blind deconvolution (BD) algorithm has been applied. As the BD methods were usually sensitive to noise, to eliminate the consequence of noise in the BD procedure, a BD algorithm has been applied to a suitable subband in the wavelet domain and to additionally improve the visual quality.

3. PROPOSED METHODOLOGY

Let $I(x,y)$ and $I^{'}(x,y)$ be the original and noisy image of size $M \times N$, i.e., $0 \le x \le M-1, 0 \le y \le N-1$, in which $I^{'}(x,y)$ is assumed to be contaminated by random noise with an intensity level of γ. The proposed technique restores the original image by removing the noise from $I^{'}(x,y)$ by performing the operations as depicted in figure 1.

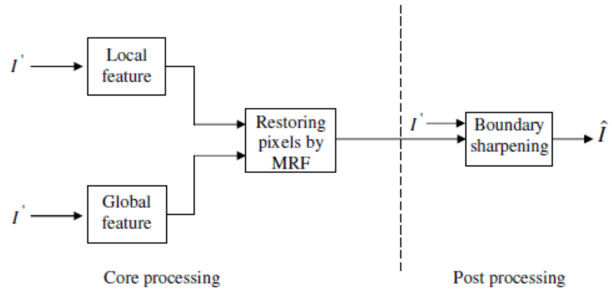

Figure 1: Structure of Proposed Heuristic Image Restoration Technique

The proposed technique is composed of two stages of operation: core processing and post processing. The core processing mainly extracts local and global features from the noisy image and restores the pixels by using MRF. The post processing is nothing but an operation of sharpening the edges of restored image and improving the quality of image. The further subsections explain the sub-individual processing units of the proposed technique.

3.1 Local Feature Extraction

In the proposed technique, the local feature of a pixel $p(x,y)$ is extracted as follows,

$$F_{loc}(x^{'},y^{'}) = \sum_{j=-R}^{R}\sum_{k=-R}^{R}\left(\frac{(p(x^{'},y^{'}) - p(x^{'}-j)p(y^{'}-k))^2}{2R+1}\right), \quad \begin{array}{l} 0 \le x^{'} \le M-2 \\ 0 \le y^{'} \le N-2 \end{array} \qquad (1)$$

Where, $p(x',y')$ is the pixel value of noisy image and (x',y') is the coordinate values of that pixel. F_{loc} and R indicates the local feature and the local range of the given pixel (x,y), respectively. F_{loc} and R has to be selected in such a way that it should satisfy the criterion.

3.2 Global Feature Extraction

The global feature represents the features related to the selected pixel, but they are not in the local region. In order to determine the global feature, local windows are defined in the images with pre-defined size. Initially, the local window is defined by selecting the random pixel values from the given image $I^{'}(x,y)$ and it is represented as w^{l} and the size of the window is represented as $m \times n$. After the w^{l} window construction, the number of windows is extracted from the image $I^{'}(x,y)$ with the same size of window w^{l}. The number of windows are $L=\{w_i\}; i=1,\cdots I$ where, I is the number of windows and the size of the windows is represented as $m \times n$. The global feature extraction process is described in the following pseudo code.

Input: $I^{'}(x,y)$ with the number of windows w_i.

Output: $F_{glo}(x^{'},y^{'})$

Step 1: Compute Correlation Coefficient between the windows w_i and window w^{l} as follows,

$$E^{i}=\frac{\sum_{x}\sum_{y}((w^{l})_{xy}-\mu(w^{l}))((w_i)_{xy}-\mu(w_i))}{\sqrt{\left(\sum_{x}\sum_{y}((w^{l})_{xy}-\mu(w^{l}))^{2}\right)\left(\sum_{x}\sum_{y}((w_i)_{xy}-\mu(w_i))^{2}\right)}} \quad (2)$$

In Equ. (2) E^{i} is the correlation coefficient value of the window w_i.

Step 2: Repeat step1 up to $i=1,\cdots I$.

Step 3: Select a window w_i which has the less correlation coefficient E^{i} value.

Step 4: Compute mean value M_i, M^{l} for w_i and w^{l} respectively.

Step 5: $d_i=(M_i-w_i)\ \&\ d^{l}=(M^{l}-w^{l})$ (3)

Step 6: $F_{glo}(x^{'},y^{'})=\sum(d_i * d^{l})$ (4)

Now, each pixel values of $I^{'}(x,y)$ image have two features namely, local and global. Then, each pixel feature values are given to the Markov Random Field (MRF) for obtaining a noise removed pixel value. A brief explanation of the MRF is given below.

3.3 Renovate Pixel value by MRF

In Markov Random Fields (MRF), a well-known Markov-Gibbs correspondence is used. Here, we have considered a neighborhood system of the eight nearest neighbors. One benefit of this approach is that no transition probabilities need to be stored or transmitted. Same random filed model is employed for all images. MRF can be completely described through a Gibbs distribution. In this paper, the local and global features $F_{loc}(x^{'},y^{'})$ and $F_{glo}(x^{'},y^{'})$ are exploited in the MRF. The probability $p_{new}(x',y')$ for an element of a Markov random field can be written as

$$p_{new}(x',y')=Z^{-1}e^{-\frac{1}{2}U(x',y')} \quad (5)$$

In Equ. (5), $p_{new}(x',y')$ is the new pixel value, Z is the partition function, $U(x',y')$ is the energy function and T is the temperature. The energy function $U(x',y')$ is the sum of all cliques belonging to the neighborhood of (x',y'). The energy function can be written as,

$$U(x',y')=\left(\sum_{v=1}^{V}C_{v}^{I'}\right)*F(x',y') \quad (6)$$

$$F(x',y')=F_{loc}(x^{'},y^{'})+F_{glo}(x^{'},y^{'}) \quad (7)$$

Where, $C_{v}^{I'}$ represents v number of cliques in the noisy image I' and $F(x',y')$ is the feature value of the pixel at the position (x',y').

3.4 Image Boundary Sharpening

The restored image obtained from the above core processing is subjected to the image boundary sharpening process, because the quality of the obtained image is low and the edges of the image are not clear. To get the sharp edge image, a morphological dilation operation is applied to the restored image. The morphological dilation operation improves the image boundaries quality. After this morphological operation, image has sharp boundaries. All the aforementioned process has proved that the noise images are restored more effectively by achieving higher image restoration ratio.

4. RESULT AND DISCUSSION

The proposed heuristic image restoration technique is implemented in the working platform of MATLAB version 7.12.0 (R2011a). The input image is restored using the proposed heuristic technique based on the features extraction and MRF method. The sample input image used in the proposed technique is shown in the figure 2.

Figure 2: Sample Input Image

The proposed technique noise added image is shown in figure 3. The input image noise is the random noise.

Figure 3: Noise Added Image

From this random noise added images the local and global features are extracted. The both local and global features are extracted for each pixel values in the input noisy image. The each pixels local and global feature is given to the MRF to acquire the restore pixels. The obtained restored pixel values are replaced to the pixel values in noisy image. Subsequently we get the restored image as an output is shown in figure 4.

Figure 4: Restored Image

Figure 4 shows the restored image of the proposed heuristic image restoration technique with high PSNR ratio. The performance analysis of the heuristic image restoration technique is described in the following section.

4.1 Performance Analysis

The performance of our heuristic image restoration technique is analyzed by adding more number of input images. To accomplish the performance analysis process, we utilized 15 number of images (11 images are natural and remaining 4 are medical images). The sample 15 input images are shown in figure 5. The random noise is added to those 15 images and those noisy images corresponding to PSNR values are shown in Table 1.

Table 1. Noisy images with their PSNR values

Random Noisy Images	PSNR Values
1	21.2135
2	21.2479
3	22.116
4	22.0755
5	22.0411
6	21.959
7	22.0011
8	21.8832
9	21.8919
10	21.7008
11	21.8665
12	22.1059
13	21.9375
14	20.6489
15	20.5364

The noise added 15 images are restored by our proposed heuristic image restoration technique and the restored images PSNR values are calculated. The restored images with their calculated PSNR values are given in Table 2.

Table 2. Restored Images with their PSNR values

Random Noisy Images	Proposed technique PSNR Values
1	22.1247
2	21.5021
3	22.6225
4	24.6294
5	21.1457
6	22.5658
7	21.2245
8	23.6857
9	23.3045
10	20.1647
11	21.5336
12	24.2088
13	22.5932
14	23.8228
15	24.509

In table 2, the PSNR mean values of restored images are higher than the noisy images PSNR mean values. The proposed technique PSNR mean value is higher than the PSNR mean value of the noisy image. The proposed image restoration technique performance is compared with the existing image restoration technique in terms of their PSNR values. The same 15 testing images of proposed technique are given to the existing image restoration technique. The image restoration performance of existing technique results are shown in Table 3.

Table 3. Existing Technique Restored Images with their PSNR values

Random Noisy Images	Existing technique PSNR Values
1	18.1968
2	19.61
3	22.4798
4	19.7149
5	21.0554
6	23.8575
7	20.8137
8	18.4182
9	22.9278
10	20.6281
11	21.0745
12	17.0802
13	21.994
14	17.7634
15	17.5862

The existing technique mean PSNR values are compared to our proposed technique mean PSNR value. The mean value PSNR values comparison shows that the existing technique provides lower performance when compared to our proposed heuristic image restoration technique. The SNR values of noisy images values are compared with the existing and proposed restored images PSNR values, which is shown in figure 5.

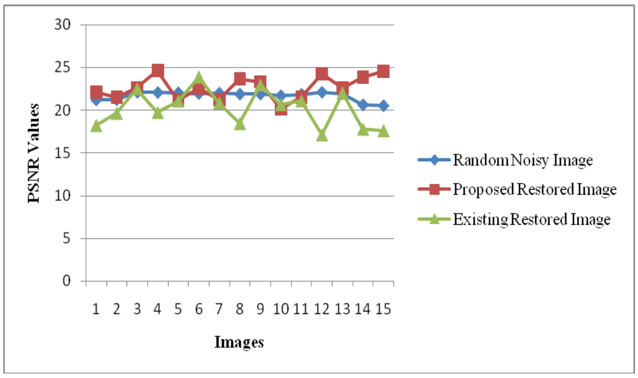

Figure 5: Comparision Graph of Proposed and Existing Method Performance

The comparison graphs shows that our proposed heuristic image restoration technique has produced restored image with high PSNR ratio than the existing image restoration technique. The PSNR values of restored image of existing method are approximately equivalent to the PSNR value of noisy image. Hence, our proposed heuristic image restoration technique has the high level restoration PSNR ratio than the conventional image restoration algorithm.

5. CONCLUSION

In this paper, the proposed heuristic image restoration technique was illustrated in detail with implementation results. In the proposed methodology, the image restoration was done using two features extraction and MRF. After that the restored image quality was improved by the post processing method. All this process has improved the performance of the restoration technique. The results have shown that the proposed heuristic image restoration technique has achieved higher PSNR values than the existing restoration technique. Thus, our proposed heuristic image restoration technique has offered better performance in restoration of noisy images with higher restoration PSNR ratio. The proposed heuristic image restoration technique was compared against existing image restoration technique to prove the image restoration performance. The proposed heuristic image restoration technique achieves high PSNR ratio in noise images than the existing image restoration technique. This declares that the proposed heuristic image restoration technique is more effective in image restoration and it can be more appropriate.

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