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Comprehensive Review of De-noising Techniques in Image Restoration

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Abstract: Wall paintings are an esteemed symbol of culture. Their restoration and preservation is one of the needs of the hour so that future generations of the world could see and learn from our culture. Paintings can lose some points on the image to white spots which are very important to be recovered to maintain the overall good visibility of the image. Existing restoration algorithms like Nearest Neighbour Method mainly take care of the local deformities and white spots. However the problem of fading is not addressed properly by the method. There is a need of an algorithm which can along with removing white spots and local deformities improve the overall quality of the image from fading point of view. White spots along with fading are very important to be recovered because fade and dull images does not have a taste of the originality and meaning of the painting. We propose an algorithm based on nearest neighbour method to address both the above mentioned issues. Experimental results confirm the efficiency of the proposed algorithm.

Keywords: ***Image Filtering, Denoising Technique, Image Restoration, Gaussian Noise, Salt and Pepper Noise, Speckle Noise.***

I. INTRODUCTION

A digital image can be described as two dimensional images as a finite set of discrete values, known as picture elements or pixels. Noise is an unwanted function that adds to image degrades its quality. Noise may come in many forms such as motion blur, noise, and camera mis-focus. Image restoration is different from image enhancement in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer, but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbor procedure) provided by "Imaging packages" use no a priori model of the process that created the image. With image enhancement noise can effectively be removed by sacrificing some resolution, but this is not acceptable in many applications. In a Fluorescence Microscope resolution in the z-direction is bad as it is. More advanced image processing techniques must be applied to recover the object. It is concerned with filtering the observed image to minimize the effect of degradations. Effectiveness of image restoration depends on the extent and accuracy of the knowledge of degradation process as well as on filter design. Image restoration differs from image enhancement in that the latter is concerned with more extraction or accentuation of image features. Image restoration is the task of minimising the degradation in an image i.e. recovering an image which has been degraded due to presence of noise and the original scene is not clear. Due to certain imperfections in the imaging or capturing process, the captured image is a degraded version of the original scene. The idea of restoration of such degraded images has become an important tool for many technological applications such as space imaging, medical imaging and many other post- processing techniques. In some cases noise gets intruded in the image at the time of acquisition. Thereby receiver in many cases receives images with diminished quality. Therefore, images received require processing before they can be used in various applications. Image restoration or denoising is required, to make a visually high quality image which include the process of changing, correcting, or moving of the image data to produce noise free image. In this paper restoring of images which contain noise has been done by using Nearest Neighbour Algorithm and scale invariance high fidelity. Nearest Neighbour involves use of nearest neighbour 8 pixels Intensity to help restoring original image. SIHF makes use of different scale variation of intensity in image. This variance in scale is smoothed by providing the average intensity to all pixels in area of scale invariance.

II. DENOISING TECHNIQUES

A. Nearest Neighbor Algorithm

Nearest neighbour interpolation is the simplest approach to interpolation. Rather than calculate an average value by some weighting criteria or generate an intermediate value based on complicated rules, this method simply determines the "nearest" neighbouring pixel, and assumes the intensity value of it.

We can see that for each data point, xi, between our original data points, x1 and x2, we assign them a value f(xi) based on which of the original data points was closer along the horizontal axis.
Now, extending this to 2D, assume that we want to re-size a tiny, 2×2 pixel image, X, as shown below, so that it "fits" in the larger 9×9 image grid, Y, to the right of it.

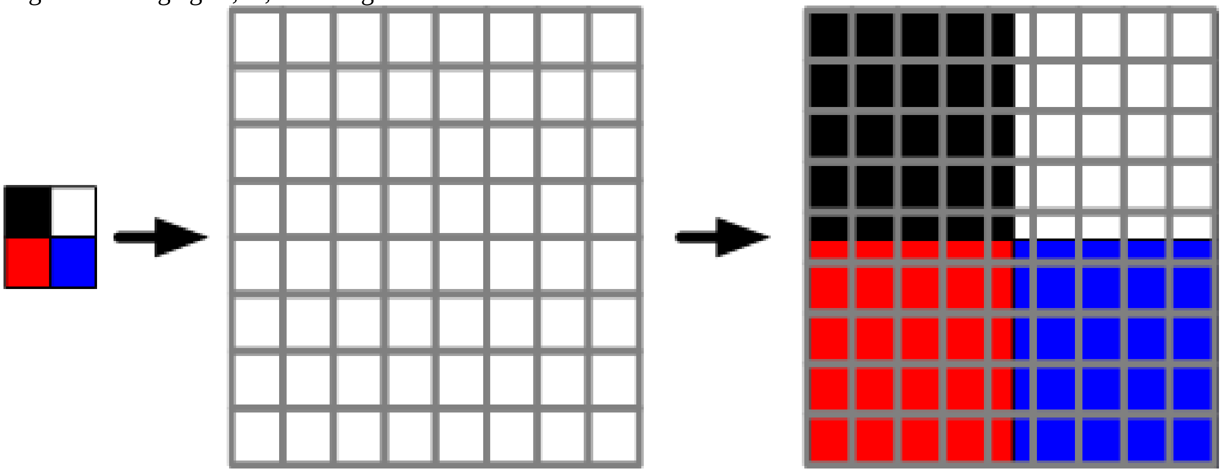

Figure 1: Example of Up sampling an Image by a Non-Integral Factor

As shown above, when we resize by a non-integral factor (as outlined in the beginning of this section on interpolation) pixels cannot simply be cloned by column/row – we need to interpolate them. The squares (representing pixels) forming a vertical and horizontal line through the rightmost image, for example, cannot contain different colour values. They can only contain a single colour value. To visualize nearest neighbour interpolation, consider the diagram below. The data points in the set X represent pixels from the original source image, while the data points in the set Y represent pixels in our target output image.

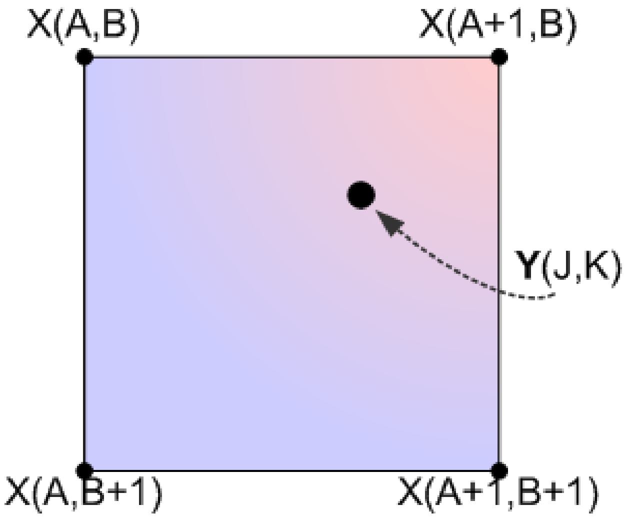

Figure 2: Coordinate System

So, for each pixel in the output image Y, we must calculate the nearest neighboring pixel in our source image X.
Furthermore, we should only need to rely on 4 specific data points: X (A, B), X (A+1, B), X (A, B+1), and X (A+1, B+1)

B. Scale Invariance High Fidelity

One of the most notable properties of natural image statistics is scale invariance, it is exhibited as:
Q [Ø□(*x*)] □□*Q* [α□□Ø□α□*x*)] (1)
Where *Q* [*φ (αx)*] is any ensemble statistic of *φ(x)* of scale *α* and *v* is a universal exponent [2] many regions are extremely similar in the image. According to the observation of more images across scale, it can be seen that more or less extremely similar regions exist between the large scale images and the small scale images, which means that there are same contents of same scale throughout scales of an image. Constrain the means and covariance matrices during learning. In contrast, we do not constrain the model in anyway — we learn the means, full covariance matrices and mixing weights over all pixels, as follows:

$$p(x) = \sum_{k=1}^{n} \pi_k N(x \mid \mu_k, \Sigma_k) \qquad (2)$$

Where *πk*, *μk* and *Σk* are mixing weight, mean and covariance matrix respectively in *k-th* component. These parameters are trained from origin scale image patches by Expectation Maximization (EM) algorithm.

III. PROPOSED METHODOLOGY

We have compared the denoising techniques on different noisy images based on the following methodology. Our algorithm is based on nearest neighbour method. A high resolution copy of the image to be restored is taken and processed. Nearest neighbour method is used to find out the white spots at local deformities. These local deformities as well as unwanted cracks in the painting are identified. The overall contrast and saturation of the image is raised to improve the results of deformity analysis. Once the deformities are detected a window of 3x3 is taken and using the method of nearest neighbour pixels the mean of colour is calculated for the deformed pixel taking into consideration the properties of all the neighbour pixels. For the pixels at the boundary of a particular image, the neighbour pixels within the boundary of the image are considered for calculating the mean. Once the image is restored by the nearest neighbour method, the contrast and saturation are readjusted to diminish the dullness of the image.

STEP I: DATA CREATION AND IMAGE PREPROCESSING

1) Dataset Creation

Collect an Image which degraded due to noise

2) Pre-processing

Pre-processing is required to improve the quality of data in image that increases features of image for further stages of operation. Let us assume that the greyscale conversion of original image be ans (i, j). Following pre-processing steps are applied to the scanned character images and their results are shown in the below given snapshots:

(1)Visual compression: We choose six intensity level l1, l2, l3, l4, l5, l6 to compress the image .in this process we assign all pixel with intensity less than t1 level to l1. Then the pixel with range from t1 to t2 with l2 intensity level again then, pixel with range from t2 to t3 with l3 intensity level and process goes on same for next three ranges. Here ans (i, j) is image before visual compression.

```
If (ans (i, j) <t1)
    a (i, j) =l1;
else if (ans (i, j)>t1 && ans (i, j) <t2)
    a (i, j) =l2;
else if (ans (i, j)>t2 && ans (i, j) <t3)
    a (i, j) =l3;
else if (ans (i, j)>t3 && ans (i, j) <t4)
    a (i, j) =l4;
else if (ans (i, j)>t4 && ans (i, j) <t5)
    a (i, j) =l5;
else if (ans (i, j)>t5 && ans (i, j) <t6)
    a (i, j) =l5;
end;
```

(2)Binarization: Before Binarization the RGB character image is changed into gray scale image and then Binarized.

Step II nearest Neighbour Algorithm and Increase Contrast and saturation

1) Nearest Neighbour algorithm

An algorithm is given here that carries out an iterative process to find the mean intensity and replace the noisy pixel. Consider an input processed image. Pixel at a position (i, j) in the input image is defined. Probability of occurrence of each neighbour of Im (i, j) is calculated. We consider a window of 3x3, then for N=1 (N is the position of nearest neighbour; N=1 means the pixels immediately adjacent to Im (i, j)), for a total of eight neighbours in that window, the mean value is obtained by using the following expression [10]

$$M = \sum_{i=1}^{N} x_i \, p\,(x_i) \quad [12]$$

The value of M gives the mean of all neighbouring points of a particular pixel (called the "good pixel value"). The central defected pixel is replaced by this good pixel value. The process carried out for Chessboard distance and City-block distance transforms separately

2) Increasing contrast and saturation:

(1)Contrast:

Increasing the contrast will result in the change of the values of pixels such that every pixel will attain a clear-enhanced value of its colour which will help in calculating the previous value of colour pixel.

(2)Saturation:

Saturation in images increases the colour value such that portions of the image get segmented according to the maximum values of the pixels in the vicinity. This also helps in determining the value of the missing pixel accurately with the help ofnearbypixels.

Both of the above contrast and saturation together will help us in determining the real value of the pixels in the images. These pixels value with nearest neighbour method will calculate the values of missing pixel.

Step III: Identifying/ Calculating no. of white spots and cracks

We find out noise in degraded image .this noise is in form of cracks and white spots. We identify cracks on basis of threshold of greyscale image contour.

1) If the size of contour is less than the threshold size then it is considered as crack.
2) On other hand if size of contour is greater than threshold size then we need to further check its width and height and,
3) If any of them is greater than threshold the n it is considered as crack
4) Otherwise if height is less than threshold it is considered as white spots.

STEP IV SIHF (SCALE IN-VARIANCE AND HIGH-FIDELITY)

A natural image always contains the same contents of different scales and the same contents of same scale exist throughout scales of the image. This describes model of the natural image paths distribution to describe the scale invariance .This offers powerful mechanism of combining natural images scale invariance and nonlocal self-similarity simultaneously to ensure a more reliable and robust estimation. This technique of SIHF is described as follows:

1) This involves setting threshold for pixels where estimation by SIHF is required .This is set by location of cracks and white spots to be filled.
2) Then, creating an array by extending in all direction by m pixels.
3) It will create an array of 2m+1 x 2m+1.
4) Pixel intensity of this array is summed and average intensity is calculated.
5) To ensure smoothness, this average intensity is providing to this array.

STEP V: CALCULATE PSNR

Comparing restoration results requires a measure of image quality. Two commonly used measures are *Mean-Squared Error* and *Peak Signal-to-Noise Ratio*. The mean-squared error (MSE) between two images g (x, y) and $\hat{g}$ (x, y) is:

$$E_{MSE}=1/MN\sum_{n=1}^{M}\sum_{m=1}^{N}[\hat{g}(n, m) - g(n, m)]^2 \quad (3)$$

One problem with mean-squared error is that it depends strongly on the image intensity scaling. A mean-squared error of 100.0 for an 8-bit image (with pixel values in the range 0-255) looks dreadful; but a MSE of 100.0 for a 10-bit image (pixel values in [0,1023]) is barely noticeable.

Peak Signal-to-Noise Ratio (PSNR) avoids this problem by scaling the MSE according to the image range:

$$PSNR= -10\log_{10} e_{MSE}/S^2 \quad (4)$$

where S is the maximum pixel value.

PSNR is measured in decibels (dB). The PSNR measure is also not ideal, but is in common use. Its main failing is that the signal strength is estimated as S^2, rather than the actual signal strength for the image. PSNR is a good measure for comparing restoration results for the same image, but between-image comparisons of PSNR are meaningless.

IV. PSEUDO CODE

Step 1: Get an input image by degrading the image with noise.
Step 2: Get visually compressed conversion of gray scale image of the Degraded Image. Let name of Input Image be I.
Step 3: Get the binarized Image Ib=Binarized image by converting the visually compressed image into black and white; \\ image with cracks and white spots segmented as white
Step 4: Get the size of Ib in (i, j) =size (Ib); \\ get dimensions of Ib
Step 5 : start the for loop of i = 1 -> imax where i is width coordinate position of pixel in image and imax is maximum value of width coordinate.
Step 6: start nested for loop j = 1 -> jmax where j is height coordinate position of pixel in image and jmax is maximum value of height coordinate.
Step 7: if (Ib ((i, j)) ==white) here contour threshold is used to identify cracks or white spots
Step 8 : I((i, j))=I(i-1,j) Restoring from nearest neighbor in degraded image I in which contrast and saturation have also been enhanced.
Step 9: end if;
Step 10: end nested for loop;
Step 11: end for loop;
Step 12: start the for loop of i = 3 -> imax where i is width coordinate position of pixel in image i and imax is maximum value of width coordinate.
Step 13: start nested for loop j = 3 -> jmax where j is height coordinate position of pixel in image and jmax is maximum value of height coordinate.
Step 14: if (I (I, j)>Io) where Io is threshold Intensity
Step 15: Get array of 5x5 by taking 2 pixels above and below the ((i, j)) position and in same way 2 pixel left and right from position ((i, j));
Step 16: Get sum of all intensity of pixels in this array.
Step 17: Calculate Average Intensity.
Step 18: Set the intensity of this array to Average Intensity.

Step 19: end if
Step 20: end nested for loop;
Step 21: end for loop;
Step 22: Calcualte and show histogram of the restored image using NN and SIHF.
Step 23: Calculate value of PSNR using NN and SIHF.

V. SIMULATION RESULTS

A. Comparision Of Image Restoratipon Using Nn And Sihf

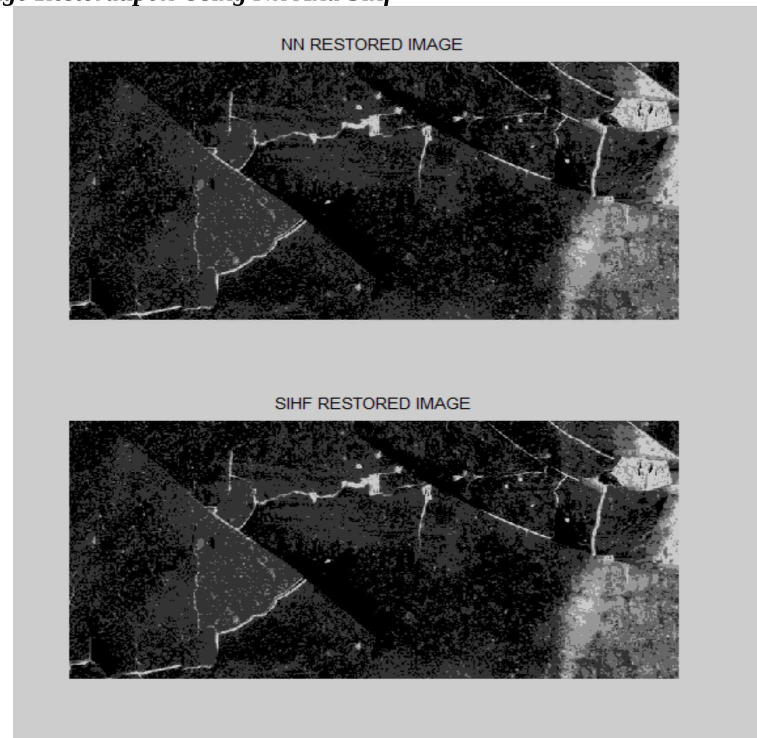

Figure 3: Comparison of image restoration using NN and SIHF

In this SIHF algorithm, natural image scale invariance and nonlocal self similarity are utilized simultaneously. More specifically, multi-scale similar patches are searched, adjusted by GMM and then 3-D transformed. In regularization-based framework, local total variation regularizer and nonlocal adaptive 3-D scale invariant sparse representation regularizer are introduced into the minimization function. Experimental results show that the proposed algorithm achieves more significant performance than the current state-of-the-art schemes.

B. Comparision Of Histogram Of Nn And Sihf

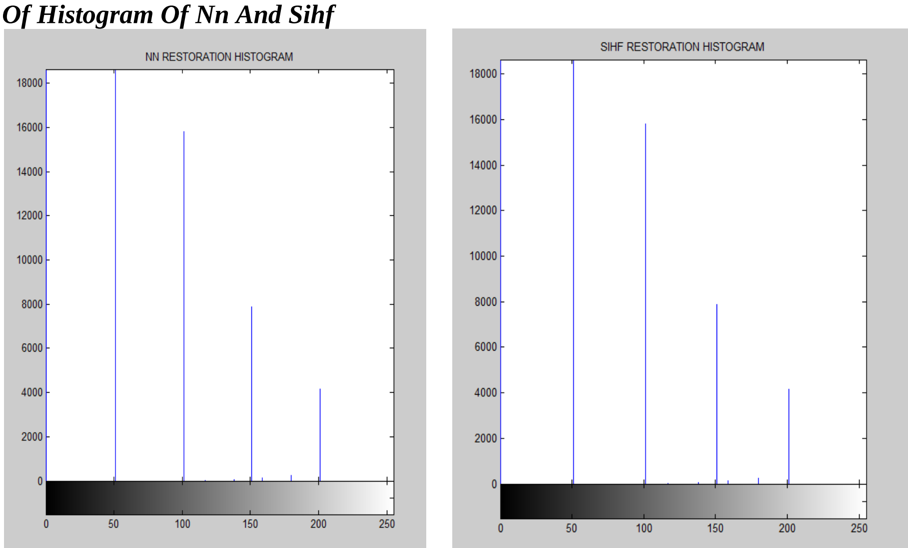

Figure 4 (a) and (b): Histogram of NN and SIHF

Histogram of Restored Image SIHF is being compared with restored image using NN histogram .This comparison show difference in intensity level ranging from 0-255 and no of times a particular intensity level is being repeated of the two algorithms.

C. Comparision Of Psnr Value Of Nn And Sihf

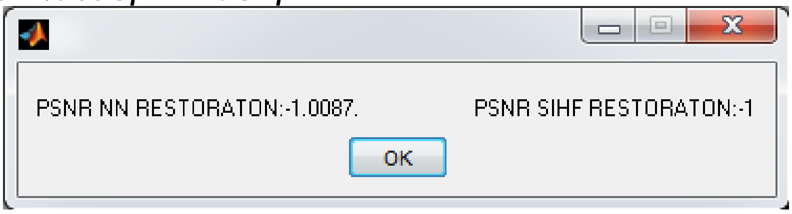

Figure 5: PSNR value of Restored Image Using NN and SIHF

To evaluate the performance of our algorithm, we mainly compare it with NN; three test images are evaluated using proposed Algorithm. Figure 3 lists the results of two image restoration algorithms on the test image. It can be seen that the proposed algorithm is more outstanding than the other one; the average result of the proposed approach is even higher than the best result of the other algorithm

VI. CONCLUSION AND FUTURE WORK

The simulation results showed that the proposed algorithm performs better than the nearest neighbor method. The detection of deformities is enhanced in case of our algorithm by adjusting the contrast and saturation of the image. Apart from removing the local deformities and white spots from the image the overall appearance of the image is enhanced significantly by reducing the fading. Cuts and fold-marks in images are also detected and removed that give a smoother appearance to the image.

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