

A brief review on image restoration in image processing

Sangita S L¹, Dr.S.S.Kanade²

PG Student ME (E&TC)¹, HOD (E&TC), TPCT's COEO²

Abstract: Image restoration is an important process in image processing. It is a process to recover image from distorted to its original image. The restoration of degraded images can be applied in many application areas that are needed to repair images. Image interpolation is one part of image restoration. There are different sources of noise in a digital image. For example, dark current noise is due to the thermally generated electrons at sensing sites; it is proportional to the exposure time and highly dependent on the sensor temperature.

Keywords: Image Interpolation, Genuine fractals, nearest neighbour, bilinear, bicubic, spline.

I. INTRODUCTION

Information about final paper submission is available from the conference website. Shot noise is due to the quantum uncertainty in photoelectron generation; and it is characterized by Poisson distribution. Amplifier noise and quantization noise occur during the conversion of the number of electrons generated to pixel intensities. The overall noise characteristics in an image depend on many factors, including sensor type, pixel dimensions, temperature, exposure time, and ISO speed. Noise is in general spatial position and channel dependent. Blue channel is typically the noisiest channel due to the low transmittance of blue filters. In single-chip digital cameras, demosaicking algorithms are used to interpolate missing color components; therefore, noise is not uncorrelated for different pixels. An often neglected characteristic of image noise is the spatial frequency. Denoising images can be achieved by a spatial averaging of nearby pixels. This method removes noise but creates blur. Henceforth, neighborhood filters, which perform an average of neighboring pixels under the condition that their grey level is close enough to the one of the pixel in restoration, creates shocks and staircasing effects. Buades et al. [1] performed an asymptotic analysis of neighborhood filters as the size of the neighborhood shrinks to zero. His paper proved that these filters are asymptotically equivalent to the Perona-Malik equation [2], one of the first nonlinear PDE proposed for image restoration. In continuation, he proposed an extremely simple variant of the neighborhood filter using a linear regression instead of an average. By analysing its subjacent PDE, the artifacts can be eliminated. Elad et al. [3][4][5] addressed his approach based on sparse and redundant representations over a trained dictionary. Kernel regression

is also a popular state-of-the-art method for image denoising. Takeda et al. [6] made contact with the field of nonparametric statistics and adapt kernel regression ideas for use in image denoising, upscaling, interpolation, fusion, and more. Patch-based approach [7] is proposed by Kervrann et al. The method is based on a point-wise selection of small image patches of fixed size in the variable neighborhood of each pixel.

II. IMAGE INTERPOLATION FRAMEWORK USING NON-ADAPTIVE APPROACH

Image restoration is an important process in image processing. It is a process to recover image from distorted to its original image. The restoration of degraded images can be applied in many application areas that are needed to repair images. Image interpolation is one part of image restoration. Image interpolation is a process that converts from one resolution to another without losing the visual content in the picture. Image interpolation process is often used in many application areas. The widely used areas are viewing and magnifying satellite images and online images, seeing clearly the face of specific member from the historical group photo, identifying a license plate or a face in law enforcement, analysing patient's CT scanned image in medical imaging, etc.

Above all the processes need to enlarge image size to see the detailed information. When the small size images are enlarged, it is very important to get sharper or clearer images. Many photo editing software have not been developed images with clear information. To see the detailed information in images is an essential for many application areas such as medical imaging, criminal and satellite photo analysis.



III. INTERPOLATION METHODS

Interpolation works by using known data to estimate values at unknown points. There are two kinds of image interpolation. Interpolation from a higher resolution to a lower resolution is referred as down-scaling or down sampling. On the other hand, interpolation from a lower resolution to a higher resolution is called up-scaling or up sampling. Interpolation algorithms can be grouped into two categories: adaptive and non-adaptive. Adaptive methods change depending on what they are interpolating (sharp edges vs. smooth texture), whereas non-adaptive methods treat all pixels equally.

Non adaptive or linear interpolation is a fixed pattern of computation that is applied in every pixel location to recover the missing components. These algorithms are simple to implement and computational requirements are much lower than adaptive methods. These types of algorithms are nearest neighbour, bilinear, bucolic, spline, sinc, lanczos and others. Depending on their complexity, these use anywhere from 0 to 256 (or more) adjacent pixels when interpolating. The more adjacent pixels they include, the more accurate they can become, but this comes at the expense of much longer processing time. Adaptive or non-linear interpolation is an intelligent processing that is applied in every pixel location based on the characteristics of image in order to recover the missing components. There are many proprietary algorithms in licensed software such as: Image, Photo Zoom Pro, Genuine Fractals and others. Many of these apply a different version of their algorithm (on a pixel-by-pixel basis) when they detect the presence of an edge-- aiming to minimize unsightly interpolation artefacts in regions where they are most apparent. These algorithms are primarily designed to maximize artefact-free detail in enlarged photos, so some cannot be used to distort or rotate an image. Nearest neighbour is the most basic and requires the least processing time of all the interpolation algorithms because it only considers one pixel-- the closest one to the interpolated point. This has the effect of simply making each pixel bigger. Bilinear interpolation considers the closest 2x2 neighbourhood of known pixel values surrounding the unknown pixel. It then takes a weighted average of these 4 pixels to arrive at its final interpolated value. This results in much smoother looking images than nearest neighbour.

All non-adaptive interpolators attempt to find an optimal balance between three undesirable artefacts: edge halos, blurring and aliasing. Even the most advanced non-adaptive interpolators always have to increase or decrease one of the above artefacts at the expense of the other two-- therefore at least one will be visible. Also note how the edge halo is similar to the artifact produced by over sharpening with an unshp mask, and improves the appearance of sharpness by increasing acutance. Adaptive interpolators may or may not produce the above artifacts; however they can also induce non-image textures or strange pixels at

small-scales. On the other hand, some of these "artifacts" from adaptive interpolators may also be seen as benefits. Since the eye expects to see detail down to the smallest scales in fine-textured areas such as foliage, these patterns have been argued to trick the eye from a distance (for some subject matter).

IV. NL MEANS INTERPOLATION FILTER

We use this filter to get clearer and sharper interpolated image. It is adaptive nature. In this filter, v is used as initialization image. To interpolate, we compare neighborhood pixels in u0 and v. NL means compare neighborhood throughout the whole image. To get interpolated image, NL means interpolation filter is as follow:

$$u(x) = \frac{1}{z(x)} \int_{\eta_2 u_0} \left(y \right) \exp \left(- \frac{\left\| v(Nk(x)) - N_1 \left(N_2(y) \right) \right\|_2^2}{\lambda^2} \right) d y \cdot x^{\epsilon \cap x} \quad 1$$

where, $u(x)$ is our goal (output) image. $(Nk(x))$ and

$N_1(y)$ are neighborhoods of pixel values $u(x)$ and

$\int_{\eta_2 u_0} (y)$ z(x) is the normalization factor as follows.

$$z(x) = \int_{\eta_2} \exp \left(- \frac{\left\| v(NE(x^2)) - u_2 \left(N_2(y) \right) \right\|_2^2}{n^2} \right) d y \quad 2$$

$$z(x) = \int_{\eta_2} \exp \left(- \frac{\left\| v(NE(x^2)) - u_2 \left(N_2(y) \right) \right\|_2^2}{n^2} \right) d y \quad 2$$

In NL means filter, we defined weight value to get more fined image. To adjust the filter, weight determined by adaptive anisotropically weighted similarity function. So, the filter becomes as follows



$$u\left(\overset{-}{\mathbf{x}}\right)=\frac{1}{z\overset{-}{\mathbf{x}}}\left(\int\cap_2 u_o\left(\overset{-}{\mathbf{y}}\right)\exp\left[-\frac{\psi(K\theta)\left\|v\left(N_k\left(\overset{-}{\mathbf{x}}\right)\right)-u_o\left(N_1\left(\overset{-}{\mathbf{y}}\right)\right)\right\|_2^2}{\eta^2}d\overset{-}{\mathbf{y}}\right),\overset{-}{\mathbf{x}}\in\cap_K \quad 3$$

$\psi(K, \theta)$ is defined as follows.

$$\psi(K\theta)=\frac{1}{2\sigma(K)\sigma_2(K)}\in^{-\beta} \quad 4$$

Where, θ is orientation.

V. Experimental results

The suggested modifications to the image denoising methods significantly improve visual quality of the resulting images by reducing the Gibbs phenomenon (ringing and noise residuals around edges) and suppressing a low-frequency noise. The results of our multiresolution adaptive PCA algorithm can be found in [5]. We have tested the modified NL means method on video sequences and registered the improvements.

V. CONCLUSION

We have proposed the multiresolution variants of two state-of-the-art image denoising algorithms and achieved the improvement in visual quality (reduction of Gibbs phenomenon and low-frequency noise) and PSNR. We suggest using this general framework for modification of other image and audio processing measure.

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