Super Resolution Using Adaptive Wiener Filter

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Abstract- The Simple Super-Resolution Algorithm is proposed using Adaptive Wiener Filter. It uses low resolution of Images to obtain the HR images. This gives computationally simple method to obtain HR images within less time. The HR Image is obtained by using a local moving window. The actual output image is compared with the Median filtered image. The size of the window is varied according to the noise added in the image. Along with the filtered Image output the corrected number of pixel values and the elapsed time is also displayed.

Keywords- Super-Resolution, Adaptive wiener filter,HR.

I. INTRODUCTION

Image Super Resolution is needed for better pictorial view for human interpretation or for machine to make correct decisions.With the increase in the pixel density of an image the information content in an image increases and also the quality of image.

Resolution is concerned with the dots per inch (dpi) and the number of pixels per inch (ppi) an image possesses. With the increase in pixel density the quality of image also increase. Whilecapturing the image variousdistortions occurs which leads to image degradations. Degradations such as Optical blur, Motion blur, Noise, Aliasing effect[4].

Optical blur-distortion is generally referred to an optical aberration that deforms and bends physically straight lines and makes them appear curvy in images, which is why such distortion is also commonly referred to as “curvilinear” (more on this below). Optical distortion occurs as a result of optical design, when special lens elements are used to reduce spherical and other aberrations. In short, optical distortion is a lens error.Motion Blur- is the apparent streaking ofrapidly moving objects in a still image or a sequence of images such as a movie or animation. It results when the image being recorded changes during the recording of a single exposure, either due to rapid movement or long exposure. Aliasing-It causes different signals to become In-distinguishable due to sampling.Noise-Different types of noise gets added in the image while capturing, examples Salt & Pepper Noise, Poisson Noise, Speckle, Gaussian etc.

Super Resolution helps to recover original image properties, which were disturbed due to the above mentioned noise. In Super Resolution multiple LR images are combined to obtain HR images.

II. APPLICATIONS

1. Surveillance video: frame freeze and zoom region of interest (ROI) in video for human perception (e.g. look at the license plate in the video), resolution enhancement for automatic target recognition (e.g. try to recognize a criminal’s face).
2. Remote sensing: several images of the same area are provided, and an improved resolution image can be sought.
3. Medical imaging (CT, MRI, Ultrasound etc): several images limited in resolution quality can be acquired, and SR technique can be applied to enhance the resolution.
4. Video standard conversion: e.g. from NTSC video signal to HDTV signal.

III. CHALLENGES

1. ComputationEfficiency-

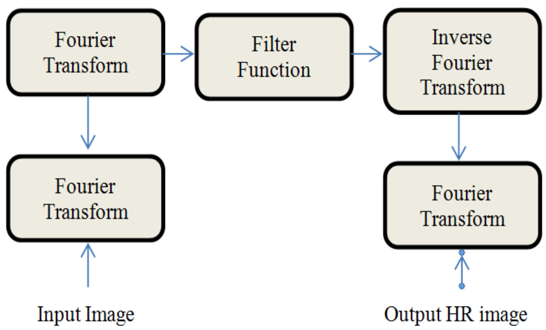
Another difficulty limiting practical application of SR reconstruction is itsintensive computation due to large number of unknowns, which require ex-pensive matrix manipulations. Real applications always demand efficiency of the SR reconstruction to be of practical utility, e.g., in the surveillance videos scenarios, it is desired for the SR reconstruction to be real time.

2.Image Registration-

Image registration is critical for the success of multi-frame SR reconstruction,where complementary spatial samplings of the HR image are fused. The image registration is a fundamental image processing problem that is well knownas ill-posed. The problem is even more difficult in the SR setting, where theobservations are low-resolution images with heavy aliasing artifacts. The performance of the standard image registration algorithms decreases as the resolution of the observations goes down, resulting in more registration errors.Artifacts caused by these registration errors are visually more annoying than the blurring effect resulting from interpolation of a single image. TraditionalSR reconstruction usually treat image registration as a distinct process fromthe HR image estimation. Therefore, the recovered HR image quality dependslargely on the image registration accuracy from the previous step.

IV. FREQUENCY DOMAIN

The Frequency Domain method is used mostly to solve the problem of Super-Resolution. The block diagram of frequency domain method is shown below:



Advantages-1.Frequency domain method enhances the details of low-resolution images spontaneously by extrapolating the high frequency details in LR images.
2. Frequency domain method has low computation.

V. SPATIAL DOMAIN

Frequency domain has some disadvantages i.e., it does not use prior knowledge, also it limits the inter-frame motion to be translation.Spatial domain overcomes these drawbacks by using prior knowledge for resolving the problem. Spatial resolution means pixel density in an image and measures in pixel per unit area. Spatial domain uses prior knowledge of image and unbind the motions between frames. The higher the spatial resolution of an image, greater the number of pixels in the image accordingly, smaller the size of individual pixels will be. This allows for more detail and subtle color transitions in an image. The spatial resolution of a display device is often expressed in terms of dots per inch (dpi) and it refers to the size of the individual spots created by the device[5].

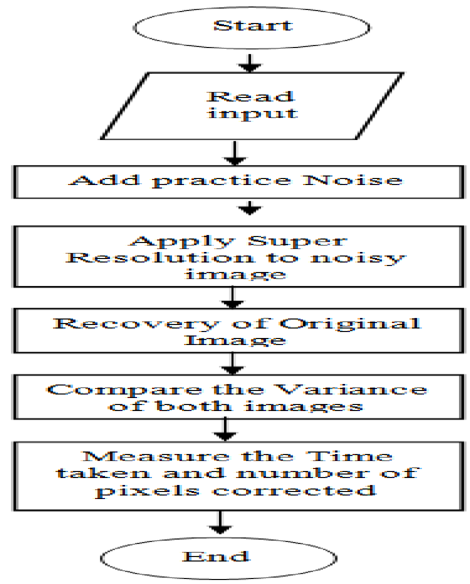
VI. MEDIAN FILTER

Median Filtering is a non-linear method used to remove noise from images. It is widely used as it removes noise while preserving its edges. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighbouring pixels. The pattern of neighbours is called the “window”, which slides, pixel by pixel, over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order,and then replacing the pixel being considered with the middle(median) pixel value.

VII. AWF

In this project, I presented a new computationally simple SR algorithm using a type of adaptive Wiener filter (AWF). The proposed AWF SR method combines non-uniform interpolation and restoration into a single weighted sum operation. In particular, the AWF SR method populates a common HR grid using the LR frames and the registration information. The proposed method does not require quantization of the LR pixel coordinates to populate a discrete HR grid. Here, we make use of the exact LR pixel locations provided by the registration algorithm. The AWF SR algorithm then produces the HR pixel estimates using weighted sums of neighboring LR pixels. The weights for each HR pixel are designed to minimize mean squared error based on the relative spatial locations of the LR pixels. In addition to avoiding the quantization of the LR pixel locations here, we use a parametric statistical model for the correlations that ultimately define the filter weights. It is this parametric model that allows the algorithm to handle non-quantized motion parameters. It also gives the system a small number of tuning parameters to control performance and eliminates the need for empirical training images and the computational burden of estimating statistics from those images. Another novel aspect of this work is that we apply a spatially varying statistical model to control the SR filter weights. Thus, the filter weights adapt spatially and temporally to changing spatial distributions of LR pixels on the HR grid, and to the local intensity statistics of those LR pixels. Since the weights adapt with distribution of LR pixels, it is quite robust and will not become unstable when an unfavorable distribution of LR pixels is observed. The proposed spatially-adaptive algorithm is simpler computationally for both training and filtering than the vector quantization approach of the PWS SR method. Note that, with or without the spatially varying statistical model, a potentially distinct and optimum set of weights is computed for estimating each HR pixel on the HR grid. This is because the spatial location of the LR pixel around each HR pixel is considered individually, allowing the filter weights to optimized for each HR pixel independently. This gives the proposed system more degrees of freedom (in the form of distinct filter weights) than the spatially invariant linear filter.

VIII. ALGORITHM



IX. METHODOLGY

Using MATLAB2016b the code is written. Graphical User Interface is launched after running the code.

1. The Input is selected from the database.
2. The required practical noise % is added to the Image example, Salt and Pepper, Gaussian Noise etc.
3. Noisy Image with added noise% and Median filtered image is displayed
4. After which the Adaptive Wiener Filter is applied. The filter is applied using window. If %noise is <=20 window size will be 3,if %noise is <=40 window size will be 5 and if %noise is <than 40 then window size will be 7.Measure the time required for AWF and the Corrected pixel numbers are displayed

Thus,I have compared Median filter results with TheAdaptive Wiener Filter.This gives the Expected High-Resolution Image along with the variance of Median filter and AWF image.

X. EXPERIMENT AND ANALYSIS

Demo1:

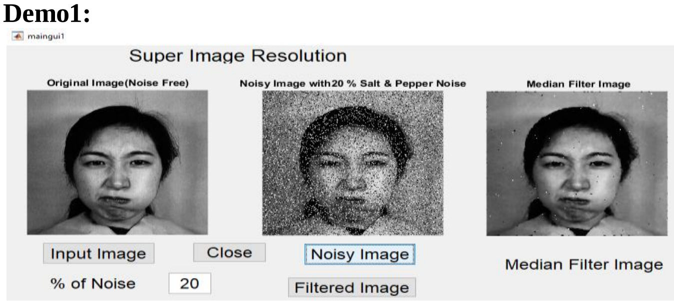


Fig.1: Demo1 image with 20% noisy image, and median filtered image

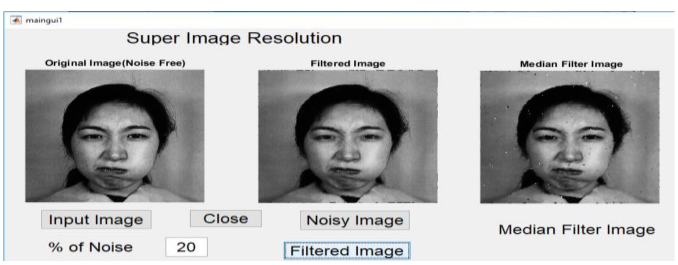


Fig.2: Demo1 image with AWF image and median filtered image

Demo2

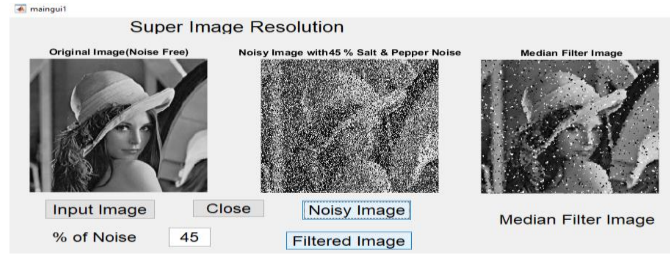


Fig.3: Demo2 image with 45% noisy image, and median filtered image

Fig.4: Demo1 image with AWF image, and median filtered image.

XI. RESULTS

Image	Noise %	Median (Variance)	AWF (Variance)
Demo1 Image	20%	0.419	0.415
Demo2 Image	45%	0.0881	0.0433

- Proposed algorithm was demonstrated successfully using MATLAB.
- Thus from the above results we can conclude that AWF gives better results than Median filter.

FURURE SCOPE:

For further improvement in the above algorithm we can work on decreasing the time of filtering and also for color images same algorithm application can be worked on.

XII. APPLICATIONS

Super-Resolution has several applications in real world. Some of them are given below.

1.Medical Science-Ultra sound, X-ray, CT, MRI

2.Biometrics-Fingerprint recognition system, Character recognition system, Face recognition, DNA Analysis.

3.Satellite Imaging- Planetary information, Weather forecasting, Traffic and target detection.

4.Entertainment- HDTV, Photography

5.Commercial-Barcode reading.

6.Surveillance video- Zooming (Detection of number plates).

7.Military-Tracking and detecting.

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