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Effective Pixel Interpolation for Image Super Resolution

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Abstract: *In the near future, there is an eminent demand for High Resolution images. In order to fulfil this demand, Super Resolution (SR) is an approach used to renovate High Resolution (HR) image from one or more Low Resolution (LR) images. The aspiration of SR is to dig up the self-sufficient information from each LR image in that set and combine the information into a single HR image. Conventional interpolation methods can produce sharp edges; however, they are approximators and tend to weaken fine structure. In order to overcome the drawback, a new approach of Effective Pixel Interpolation method is incorporated. It has been numerically verified that the resulting algorithm reinstate sharp edges and enhance fine structures satisfactorily, outperforming conventional methods. The suggested algorithm has also proved efficient enough to be applicable for real-time processing for resolution enhancement of image. Statistical examples are shown to verify the claim. Image fusion technology is also used to fuse two processed images obtained through the algorithm.*

Keywords: *Super Resolution, Interpolation, EESM, Image Fusion*

I. INTRODUCTION

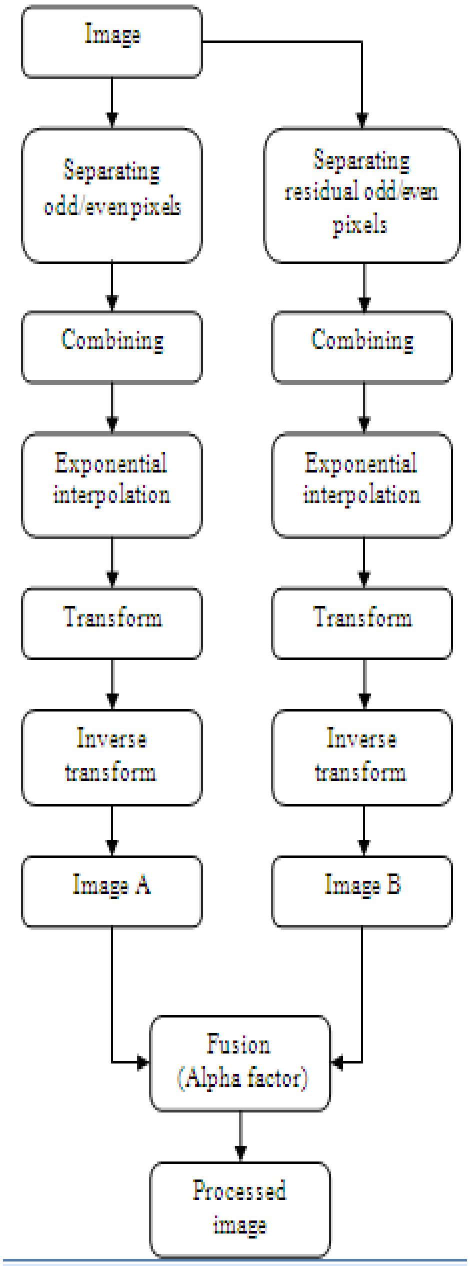
The vital aim of Super Resolution [1] is to generate a higher resolution image from lower resolution images. High resolution image tender a high pixel density and thereby more information about the original scene. The need for high resolution is widespread in computer vision applications for better performance in pattern recognition and analysis of images. High resolution is of significance in medical imaging for diagnosis. Many applications necessitate zooming of a specific area of importance in the image wherein high resolution becomes indispensable, e.g. surveillance, forensic and satellite imaging applications. On the other hand, high resolution images are not always available since the setup for high resolution imaging attest is expensive. Also it may not always be practicable due to the intrinsic boundaries of the sensor, optics manufacturing technology. These tribulations can be overcome through the use of image processing algorithms which are comparatively inexpensive and as well utilises the low resolution imaging, giving rise to perception of Super Resolution [2].

Digital images are often to be re-sampled for diverse tasks such as image generation, compression, visualization, and zooming. Image re-sampling is essential for every geometric transform of discrete images, except shifts over integer distances or rotations about multiples of 90 degrees; its first step is image interpolation. Thus image interpolation methods have occupied a peculiar position in image processing, computer vision, and communication. There are a variety of interpolation methods proposed in the literature. These methods are conventionally characterized by two kinds: linear and nonlinear ones. For linear methods, assorted interpolation kernels (polynomials) of finite size have been introduced as approximations of the perfect interpolation kernel (the sinc function) which is spatially unlimited. However, the linear methods carry out the interpolation independently of the image content and therefore they may interpolate images crossing edges, which bring in artifacts such as aliasing distortions, image blur, and/or the checkerboard effects. Nonlinear interpolation methods have been suggested in order to trim down the artifacts of linear methods [5]. The foremost step in the nonlinear methods is to either fit the edges with some templates or predict edge information for the high resolution image from the low resolution one statistically. These edge-directed methods usually result in sharper interpolated images, but occasionally suffer from rigorous visual degradation (e.g., uneven visual impression) in fine texture regions. In this paper, a new approach "Effective Pixel Interpolation for Image Super Resolution" based on the idea of Exponential Effective SINR Mapping (EESM) is proposed. EESM is used to map the instantaneous values of SINRs to the corresponding Block Error Rate (BLER) value. The basic idea of EESM is to find a compression function that maps the set of SINRs to a single value. The proposed method gives better result than other interpolation methods with good PSNR value.

II. PROPOSED ALGORITHM

High resolution refers to an image with a high level of information. In the proposed work, a practice known as Super Resolution (SR) is used to augment the resolution of an imaging system. The basic principle of the SR technique is the increase in the resolution with the obtainable multiple low resolution images. If the images are sub-pixel shifted, then each low resolution image contains independent information. So the information content is more if the SR image is formed from multiple low resolution images. Super resolution renovation from multi-frames is a comparatively new approach which super resolve a single HR frame from several LR frames (without blur). The application of SR algorithms is possible only if aliases subsist, and the images have sub-pixel shifts. There are many different SR techniques and they can be applied in the frequency domain or the spatial domain. Nevertheless, the latter provides better flexibility in modeling noise and degradation. So the analysis is centered on spatial domain.

Fig. 1 Effective Pixel Interpolation for Image Super Resolution



In this proposed system, EESM based interpolation scheme is used to create one high resolution image. Two low-resolution frames I_1, I_2 are obtained from the original image by a half-pixel shift in x and y directions. Later these frames are mapped on quincunx grid. The algorithm determines the pixel-shift between adjacent frames at sub-pixel level and the created space denotes the missing pixel in Super-resolution image. Then effective pixel interpolation is performed for interpolation. Discrete cosine transform is applied to the interpolated high resolution grid. Subsequently inverse transform is applied to the image to obtain super-resolved image. The same procedure is followed for the residual pixels. Finally the two processed images are fused using image fusion method.

A. Half Pixel Shift using Quincunx Sampling

The original image is sampled to attain two low resolution frames I_1, I_2 which are at a half pixel-shift in the *x* and *y* direction relative to one another. This shift gives sampling pattern called quincunx sampling. Quincunx sampling takes pixels in an image with purely even and odd valued indices. Frame I_1 contains the odd indices pixels and frame I_2 contains even indices pixels. Shift in two frames simulate the diagonal motion of a camera over an area, assuming CCD array of the camera samples the area in this half-pixel manner. In Super-Resolution algorithms, one low resolution pixel corresponds to a set of high resolution pixels. Each low resolution pixel corresponds to only one high resolution pixel. Fig.2 illustrates quincunx sampling by splitting of 6x6 pixel image into two 3x3 pixel images at desired half-pixel shift. Zeros indicates odd indices pixels whereas star indicates even indices pixels.

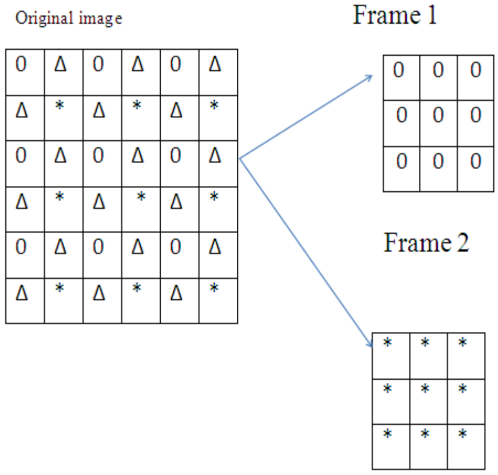


Fig. 2 6x6 Image is Split into 3x3 Pixel Images at Desired Half-Pixel Shift

B. Combining Frames on Quincunx Sampling Grid:

The high resolution grid is designated as $H(x_H, y_H)$ and the low resolution frames as $F_1(x_1, y_1)$ and $F_2(x_2, y_2)$corresponding to the frames I_1, I_2. *Tr(.)* is a transformation for combining on a quincunx grid.

$$H(x_H, y_H) = Tr[F_1(x_1, y_1), F_2(x_2, y_2)] \qquad (1)$$

x1 = 2xH-1, y1 = 2yH-1

x2 = 2xH, y2 = 2yH

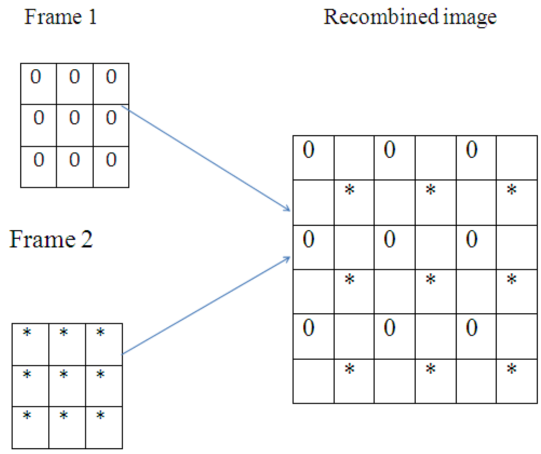


Fig.3 Combining Frames into High Resolution Grid

C. Interpolation

The missing coefficients are interpolated using different types of interpolation. In this proposed algorithm the Effective Exponential Interpolation technique is considered for image since images are affected by signal to noise ratio.

$$\rho\text{eff} \equiv EPI(\rho,\kappa) \equiv -\kappa \ln\left(\frac{1}{N}\sum_{i=1}^{N} e^{\frac{\rho i}{\kappa}}\right) \quad (2)$$

Where ρeff describes the effective pixel value ρi denotes the ith neighbouring pixel and κ describes the distance between the pixel and its neighbour. *N* describes the number of neighbouring pixels. *EPI* describes effective pixel interpolation.

D. Discrete Cosine Transform

The interpolated image is transformed using DCT. The Discrete Cosine Transform has admirable energy consumption for highly correlated images.

$$c(u,v) = \alpha(u).\alpha(v) \sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y).cos\left[\frac{(2x+1)u\pi}{2N}\right].cos\left[\frac{(2y+1)v\pi}{2N}\right] \quad (3)$$

for $u, v = 0,1, \ldots N-1$

where, $\alpha(u)\ or\ \alpha(v) = \begin{cases} \sqrt{\frac{1}{N}} & for\ u\ or\ v = 0 \\ \sqrt{\frac{2}{N}} & for\ u\ or\ v = 1,2, \ldots N-1 \end{cases}$

E. Inverse Transform

$$f(x,y) = \alpha(u).\alpha(v) \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} c(u,v).cos\left[\frac{(2x+1)u\pi}{2N}\right].cos\left[\frac{(2y+1)v\pi}{2N}\right] \quad (4)$$

for $x, y = 0,1, \ldots N-1$.

The same above procedure is being applied to the residual pixels and the two images A and B are obtained. Finally the two processed images are fused.

F. Image Fusion

Image Fusion is the process of coalesce significant information from two or more images into a single image. The resulting image will be more informative than any of the input images. The experiments are conducted using an image of size 512×512 low resolution image. Initially the image is split into two 256×256 low resolution frames using quincunx sampling. Then those images are combined into a single 512×512 high resolution image in quincunx grid. Missing coefficients are interpolated using Effective Exponential Interpolation. The same procedure is repeated for the residual pixels and the two processed images are fused using image fusion technology. Alpha is a factor that governs fusion importance of one image over the other. The experimental results show that the proposed scheme gives a better image than the conventional system.

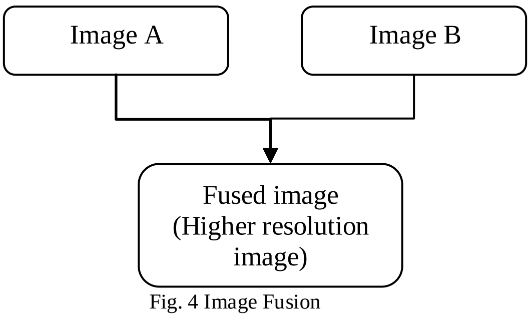


Fig. 4 Image Fusion

III. RESULTS AND DISCUSSION

The super-resolution algorithm described above is tested using the simulation tool MATLAB. The simulation results are shown below. Fig. 5 shows the shows the image taken for processing.


Fig. 5 Gray scale image


Fig. 6 Odd Pixel Image


Fig. 7 Even Pixel Image


Fig. 8 Combined Image


Fig. 9 Interpolated Image


Fig. 10 DCT Transform


Fig. 11 Image A


Fig. 12 Residual Image


Fig. 13Interpolated image


Fig. 14 DCT Transform


Fig. 15 Image B


Fig. 16 Fused Image

Fig. 6-15 shows the processing procedure and the image results obtained by processing. Fig. 17 shows the final processed image obtained via the proposed super resolution approach. Table 1 shows the statistical results obtained via the proposed processing scheme. It has been statistically found that the PSNR of the obtained via processing has an improvement to 29.4976 from 26.9298.

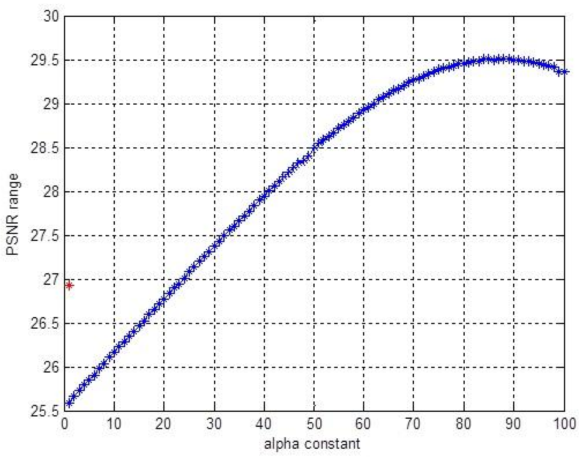


Fig. 17 Graphical Representation of PSNR vs Alpha Constant

TABLE 1: PSNR of different images

Images	PSNR Value
Original Image	26.9298
Processed Image A	29.3452
Processed Image B	29.3448
Fused Image	29.4976
Nearest Neighbour	25.2126
Exponential Averaging	29.4976

IV. CONCLUSION

In this paper Effective Pixel Interpolation based image Super-Resolution using sub-pixel shift image registration is proposed. The super-resolved image is reconstructed by registering the image frames at sub-pixel shift and interpolating the missing pixel locations using exponential averaging where original pixels are kept unchanged. Experimentation based results have shown appropriate improvements in PSNR values. The experimental results also demonstrate that a super-resolved image obtained by proposed algorithm provides fine details compared to conventional averaging system. The performance of proposed algorithm can be experimented on multiple frames from the set of same image for better results. Computational complexity of the proposed algorithm is also reduced.

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