An Efficient Image Interpolation Using Edge-error Based Sharpening

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***Abstract*—Image up-scaling is a technique for converting low resolution (LR) images to high resolution (HR) images of different size. While performing interpolation, there is some blur occurring in the high frequency (HF) region of image. So to overcome the above problem, a novel pre-processing technique based on the concept of unsharp masking is proposed. Here, the LR image is up-scaled using Lanczos interpolation method. Using the laplacian filter, the edge of the LR image and up-scaled images are calculated correspondingly. Then, the blurred HR edge is down-sample and subtracted from LR edge, to produce a sharpened edge-error image. The LR image is added to sharpened edge-error image using the concept of unsharp masking. Again, this sharpened LR image is up-scaled to give a natural look HR image. It can be observed from the result that the proposed method performs better both subjectively and objectively.**

***Index Terms*—Interpolation; Low Resolution image; Sharpening; Unsharp masking.**

I. Introduction

In the recent digital world, image up-scaling is a developing research topic. The low resolution (LR) image is converted to a high resolution (HR) image using up-scaling technique. It aims to generate HR image by preserving the texture details of LR images along with maintaining the sharpness in edge information. The HR images are used in satellite imaging, computer tomography, and video surveillance systems, where the detailed analysis of the captured images is necessary. LR images are captured due to lack of camera sensor ability to capture HR images. So to resolve this problem different hardware capacity can be increased, but image up-scaling is more economical. It is a software-based approach to produce HR image from the LR image. In multimedia communication, image compression is necessary at the transmitter side due to limitations on bandwidth and storage. On the other side, it has to be up-scaled to get back the original image. As up-scaling is a low pass filtering operation, so in recovered images, some information is lost. For overcoming the above issue, some conventional up-scaling methods have been proposed. The polynomial based methods are based on simple concepts like Bilinear [1], Bicubic [2], spline [3], and Lanczos [4] used in real-time applications. But, due to smoothness constraints, blur occurs in discontinuity regions (edge) of image. According to the human visual system, high variance regions (edge) of the image contain more information so it is necessary to recover the edges properly. For this, some edge directed up-scaling methods have been discussed in [5-10]. Commonly in edge directed interpolations, the edge orientations are computed and missing pixels are interpolated in that direction like directional cubic convolution (DCC) [5]. In DCC, the missing pixel is interpolated using cubic convolution. In new edge directed interpolation (NEDI) [6], the wiener filter concept is used. The LR image covariance is used to compute HR image covariance for producing HR image. One improved version of NEDI is soft adaptive interpolation (SAI). It is proposed by Zhang et al. [7] to interpolate a block of pixels once at a time, using the concept of least square method. But, this is not robust to outliers. So to overcome the above issues a weighted least square method has been proposed in [8], which enhances the robustness of SAI. In [9], edge pixels are interpolated in two different orthogonal directions and using a linear minimum mean square estimator (LMMSE) concept, the two results are fused to get the missing pixel value. These edge directed methods suffer from blurring artifacts.

To overcome this Giachetti et al. [10] have proposed a new method which is known as iterative curvature based interpolation (ICBI). Two basic steps are adopted for the interpolation of the missing pixels. Firstly, fast curvature based interpolation (FCBI) is used to calculate the missing pixel value. In the next step, the interpolated pixel values are iteratively corrected in a particular direction in which the derivative is minimum. The subjective quality of up-scaled image is improved in all edge directed methods, with high computational complexity. To resolve the above problem, some gradient-based methods are proposed in [11-13]. In [11], gradient similarity is used to map LR patches to the corresponding HR patches. To produce a better solution directional gradient is used as a prior. Hwang et al. [12] have used the inverse gradient of the local horizontal and vertical mask to interpolate the missing pixel in the image grid. Somehow, these gradient-based methods are lacking in maintaining the edge sharpness. Similar concept with adaptive gradient field is proposed by Song et al. [13]. Nayak et al. [14] have proposed one new concept based on similarity between LR and HR patches which restore all details in HR image. But it is very time consuming. To lessen the time and the artifacts after interpolation, iterative back projection is introduced in [15]. These methods also introduce more blurs in the edge portion of the restored HR image.

Because of this, some of the transform-based methods are proposed like wavelet transform (WT) [16-17] and discrete cosine transform (DCT) [18-19]. In the wavelet domain, the image is divided into different frequency bands. And each band is individually interpolated using bicubic interpolation followed by inverse WT to get back the up-scaled image in spatial domain. Because of this, more time is taken in WT. For improving the image quality, the DCT block-based method is used. In DCT, zero coefficients are assigned to the high frequency (HF) part of the image and take inverse DCT to get back the HR image. As it is a block-based up-scaling algorithm so blocking artifacts occur in the interpolated image and because of zero-padding the ringing artifacts appear in the HF region of the image.

As per literature, the polynomial based, edge directed based and transform-based interpolation methods suffer with (i) blurring in HF region (ii) ringing (iii) time complexity. So there is a need for a new up-scaling algorithm which is less complex along with less blurring and ringing artifacts. To solve the above problems, the proposed method introduces edge-error based sharpening method like unsharp masking. The proposed algorithm reduces the blur introduced because of the up-scaling, and the edge part of the image. The proposed method not only gives a sharpened image but also preserves the texture detail in an up-scaled image. The visual quality of the interpolated image is better compared to other state-of-art algorithms. The proposed method is presented in Section II. In Section III, the experimental results are discussed followed by a conclusion in the next Section IV.

II. Proposed Method

Due to limitation in channel bandwidth instead of sending the original image, it is down-sampled to a small size. This LR image can be computed by deletion of row and column, alternatively. On the receiver side, it is up-scaled to its original size to get back the HR image. Up-scaling is analogous to the prediction of missing pixel value at any location in the image grid, considering its neighboring pixels. So this prediction error causes blurring in the edge compared to low variance regions (smooth). So to reduce this effect of blurring, in the proposed method prediction error at edge parts is taken into consideration. The error represents the blurring introduced due to prediction. So it is added to LR image so to diminish the effect of blurring due to up-scaling.

Here, the LR image is up-scaled by the Lanczos interpolation method. Generally, because of the Lanczos method, the blurring in edges of the image is introduced. This is an inverse modeling used to combat the effect of blurring due to Lanczos interpolation. So the lost HF component during image up-scaling can be properly recovered using the proposed method. The edge region is more smooth due to up-scaling as it is a low pass filtering scheme. To overcome the effect of blurring one edge-based error method is used. The available LR image is up-scaled using lanczos interpolation method. And using a standard edge detection filter, the blurred edge is determined. Then it is down scaled at 4:1 compression ratio to get back the blurred edge after image up-scaling. The error image which represents the difference in edges before and after interpolation indicates the prediction error because of up-scaling. And it is added to the LR image to overcome the blurring in edge parts of the image.

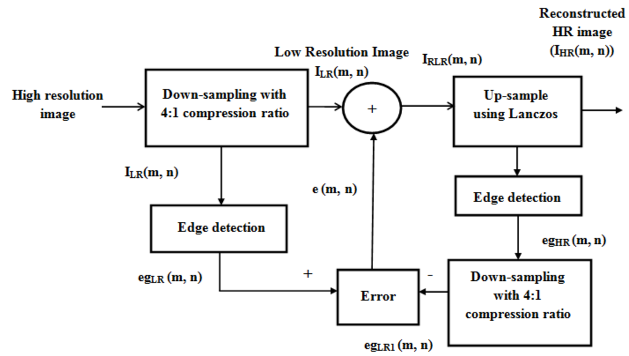


Fig. 1: Block diagram of proposed method.

A. Lanczos Interpolation

The Lanczos interpolation scheme causes the better reconstruction in texture details of the image with blurring in the edge part of the image. It is a spatial domain interpolation method which uses the sinc function. The sinc function has a main lobe along with two side lobes. The truncation of two side lobes is done by multiplying a sinc window with a sinc function. The product of sinc function with a scaled version of sinc to form lanczos window for sampling of 1D signal [20]. The lanczos interpolation for 1D signal is given as:

$$l\left(x\right)=\begin{cases} sinc\left(x\right)sinc\left(\frac{x}{s}\right) - s\leq x\leq s \\ 0 \quad otherwise \end{cases} \tag{1}$$

where s is a positive integer. And it can be assigned as 2 or 3. The number of side lobes in sinc function depends on s. The Lanczos interpolation of $s=3$ can be given as:

$$l3\left(x\right)=\begin{cases} \frac{sin(\pi x)}{\pi x}\frac{sin\left(\frac{\pi x}{3}\right)}{\left(\frac{\pi x}{3}\right)} - 3\leq x\leq 3 \\ 0 \quad otherwise \end{cases} \tag{2}$$

For a sub-sample LR image $(I_{LR}(m,n))$, the pixel value at a particular point (m_0,n_0) is given as:

$$I_{HR}\left(m_0,n_0\right)=\sum_{i=\lfloor m_0\rfloor-s1+1}^{\lfloor m_0\rfloor+s1}\sum_{j=\lfloor n_0\rfloor-s1+1}^{\lfloor n_0\rfloor+s1} I_{LR}\left(i,j\right) l\left(m_0-i\right)l\left(n_0-j\right) \tag{3}$$

where $s1$ is the size of the kernel. In the 2D image to interpolate a missing pixel in the image grid using Lanczos3, it requires 6×6 local neighbors into consideration. The final interpolated image is $(I_{HR}(m,n))$.

B. Edge detection

Because of Lanczos3 interpolation, the blur occurs in up-scaled HR image. So the standard laplacian filter is used, which emphasizes the high discontinuity region more compared to the slowly varying region. It highlights the discontinuity in the image. The laplacian kernel [21] is denoted as:

$$h_{LF} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix} \tag{4}$$

This kernel is preferred as it detects the edges of the image along with other details adjacent to the edge. The convolution of the h_{LF} with the I_{LR} produces the edge of LR image eg_{LR} and eg_{HR} can be found by convolving I_{HR} with h_{LF}.

C. Description of Algorithm

Lanczos up-scaling is used for better image reconstruction with half-pixel prediction but it results in blurred edges. To overcome the above problem, one edge-error based method is proposed. As the blurring artifacts arise in the HF part, so to reduce it one pre-processing method is proposed. Before up-scaling, the edge-error is added to the LR image. So that after Lanczos interpolation a more sharpened up-scaled image is produced. The LR image is up-scaled using Lanczos interpolation. The edge of the LR image and HR image is calculated using standard Laplacian filter. After that the up-scaled edge is down-sample at 4:1 compression ratio to the same size as LR image. The blurring introduced because of up-scaling is represented using an edge-error image. The edge-error is computed by taking the difference between the edge of the LR image and the down-sampled edge of the HR image. Then combine the LR image with a sharpened edge-error image which is a sharpened LR image, which is finally interpolated using Lanczos interpolation method.

- The LR image $(I_{LR}(m,n))$ is calculated by deleting alternative row and column of the original image.
- The HR image $(I_{HR}(m,n))$ can be obtained by up-sampling the $I_{LR}(m,n)$ at the 1:4 up-scaling using (3). The various up-scaling ratio can be taken, but here, 1:4 up-scaling is taken.
- The up-scaled edge $(eg_{HR}(m,n))$ is obtained by convolving $(I_{HR}(m,n))$ with h_{LF} as given in (4), followed by down-sampling, which is given as $(eg_{LR1}(m,n))$.
- Similarly, the edge of the LR image $(eg_{LR}(m,n))$ is calculated as given above.
- The edge-error image $e(m,n)$ is calculated by the difference between $(eg_{LR}(m,n))$ and $(eg_{LR1}(m,n))$.

$$e(m,n) = eg_{LR}(m,n) - eg_{LR1}(m,n) \tag{5}$$

- The lost HF part of the image is represented in $e(m,n)$, which is added to the $(I_{LR}(m,n))$ to get the sharpened restored LR image $(I_{RLR}(m,n))$. A weighted version of $e(m,n)$ is added to $(I_{LR}(m,n))$.

$$I_{RLR}(m,n) = I_{LR}(m,n) + k \times e(m,n) \tag{6}$$

where (m,n) represents the spatial coordinate. Different values of k cause the sharpening of the restored image. But, for lesser value of k blurring occurs in the final HR image.

- The $(I_{RLR}(m,n))$ is up-scaled using lanczos method to get back the HR image of the same size as the original image. The HR image $(I_{HR}(m,n))$ is preserved with sharpened HF and texture details, without any blurring.

III. Result Analysis

To evaluate the performance of the proposed method, several state-of-art methods are considered for comparisons like Bicubic [2], Lanczos [4], DCC [5], NEDI [6], LMMSE [9]. For subjective evaluation ten different images of different sizes are taken along with peak signal to noise ratio (PSNR) and structural similarity index (SSIM) [22] parameters are considered, for objective evaluation. PSNR (dB) indicates how much percentages of information from the original image is restored in the final HR image. If the value of PSNR is high in dB then, it indicates the better restoration ability of the proposed method. SSIM measures the similarity between original image and restored HR image. Its value lies between 0 and 1.

Table I indicates the PSNR of various interpolation methods along with the proposed algorithm for 1:4 up-sampling. Several

TABLE I: PSNR (dB) results of the 1:4 up-scaling algorithm

Method / Figure	Bicubic [2]	Lanczos [4]	DCC [5]	NEDI [6]	LMMSE [9]	Proposed
Monarch	27.193	37.134	31.197	27.473	27.032	38.456
House	27.580	36.733	32.422	29.883	29.375	37.699
Plane	27.535	37.773	33.269	29.342	29.194	38.710
Mandril	21.341	31.130	23.186	22.757	22.728	31.817
Forest	26.420	34.988	29.893	27.405	27.564	35.872
Pepper	28.442	37.575	33.319	30.651	30.720	38.427
Lena	29.650	37.688	33.328	29.997	29.802	38.478
Man	28.652	36.939	31.993	29.330	29.270	37.677
Starfish	25.748	34.552	29.204	25.814	25.400	35.740
Bike	23.027	32.554	26.319	23.774	23.617	33.536
Average	26.558	35.706	30.413	27.642	27.470	36.641

TABLE II: PSNR (dB) results of the 1:16 up-scaling algorithm

Method / Figure	Bicubic [2]	Lanczos [4]	DCC [5]	NEDI [6]	LMMSE [9]	Proposed
Monarch	21.309	22.614	21.571	21.430	23.614	25.183
House	22.880	25.266	23.993	23.951	26.555	26.897
Plane	22.905	24.526	23.535	23.240	26.169	26.575
Mandril	20.081	20.822	20.418	20.289	21.126	21.169
Forest	22.164	23.283	22.321	22.031	24.827	25.420
Pepper	24.804	25.614	24.915	24.678	28.484	28.278
Lena	25.139	25.418	24.562	24.406	27.627	28.910
Man	24.561	25.171	24.298	24.094	26.622	27.599
Starfish	20.909	21.570	20.669	20.444	22.760	24.191
Bike	19.363	20.324	19.627	19.510	20.866	21.469
Average	22.411	23.460	22.590	22.407	24.865	25.569

TABLE III: SSIM results of 1:4 up-scaling algorithm

Method / Figure	Bicubic [2]	Lanczos [4]	DCC [5]	NEDI [6]	LMMSE [9]	Proposed
Monarch	0.9223	0.9345	0.9095	0.6848	0.6919	0.9514
House	0.8393	0.8712	0.7956	0.6275	0.6311	0.8917
Plane	0.9014	0.9212	0.8981	0.6766	0.6869	0.9437
Mandril	0.6319	0.6669	0.6957	0.6582	0.6432	0.7325
Forest	0.7977	0.8424	0.8184	0.6119	0.9631	0.8713
Pepper	0.8342	0.8714	0.8380	0.6035	0.6996	0.8891
Lena	0.8435	0.8803	0.8486	0.6000	0.6006	0.9022
Man	0.8245	0.8613	0.8657	0.7749	0.6436	0.8959
Starfish	0.8505	0.8760	0.8360	0.6491	0.7772	0.9127
Bike	0.7788	0.7988	0.8386	0.7144	0.7119	0.8525
Average	0.8224	0.8542	0.8344	0.6600	0.7049	0.8843

images of different sizes have been considered. The PSNR value of the proposed scheme shows better results because of blurring artifacts reduction by sharpening the LR image before up-scaling. And proposed algorithms have 0.935 dB, an improvement over Lanczos interpolation as given in Table I.

Table II, represents the PSNR results of several algorithms over different images for 1:16 up-scaling. It clearly indicates that in higher up-scaling the performance of the proposed method is also 2.109 dB better compared to Lanczos because of edge-error.

The visual appearance of an image in human eyes is expressed as an objective parameter i.e. SSIM. If the SSIM value is close to 1 it indicates the better texture quality of output by the up-scaling method. SSIM also indicates the better edge preservation ability as given in Table III. And the proposed method shows better performance in SSIM compared to other up-scaling algorithms in 1:16 up-scaling which is indicated in Table IV.

As Fig. 2, is a combination of edge and smooth regions so it is considered for analysis. In Bicubic interpolation result (b), blur can be marked in the edge part. Boundaries are not clearly pronounced in Lanczos interpolated result (c). Some false edges are identified in (e). It can be observed in (g) the edges are clearly distinguishable. And texture details are preserved properly.

Fig. 3 is a combination of edges and smooth regions. As shown in (c) the blur occurs because of Lanczos method in the wheel parts of the image. And some staircase artifacts, in edge parts of the image, can be observed (d). In (f), fine details are lost. But, the object and background are clearly identified in (g) with better visual quality. The performance of the proposed method is also visible in Fig. 4. The restoration ability of an interpolation method can be evaluated using an error image. It indicates, how the interpolation algorithm restore the original image information. As shown in Fig. 5, the error is almost the same in (a) and (b). There are some artifacts in the texture part in (c). Error is more pronounced in (e). And in (f), error in both edge and texture part is very less. As we can observe in Fig. 5, the error image of the proposed algorithm (f) has fewer errors compared to (b). It indicates the better restoration ability of the proposed scheme both in the edge and texture part. This is because of the sharpened LR image, before up-scaling.

TABLE IV: SSIM results of 1:16 up-scaling algorithm

Method Figure	Bicubic [2]	Lanczos [4]	DCC [5]	NEDI [6]	LMMSE [9]	Proposed
Monarch	0.4791	0.7495	0.7959	0.4542	0.5140	0.8584
House	0.2975	0.6564	0.7109	0.2365	0.2881	0.7804
Plane	0.4206	0.7119	0.7459	0.3406	0.4247	0.8254
Mandril	0.2816	0.3268	0.8187	0.2034	0.2573	0.4538
Forest	0.4056	0.5903	0.6321	0.3251	0.4003	0.7222
Pepper	0.4222	0.7176	0.7389	0.3780	0.4417	0.8028
Lena	0.3892	0.6945	0.7213	0.3302	0.4136	0.8003
Man	0.3991	0.6123	0.6503	0.3192	0.4016	0.7398
Starfish	0.4063	0.5513	0.5513	0.4338	0.5395	0.7270
Bike	0.4911	0.4108	0.4108	0.3346	0.39818	0.5849
Average	0.3992	0.6021	0.6902	0.3355	0.4072	0.7295

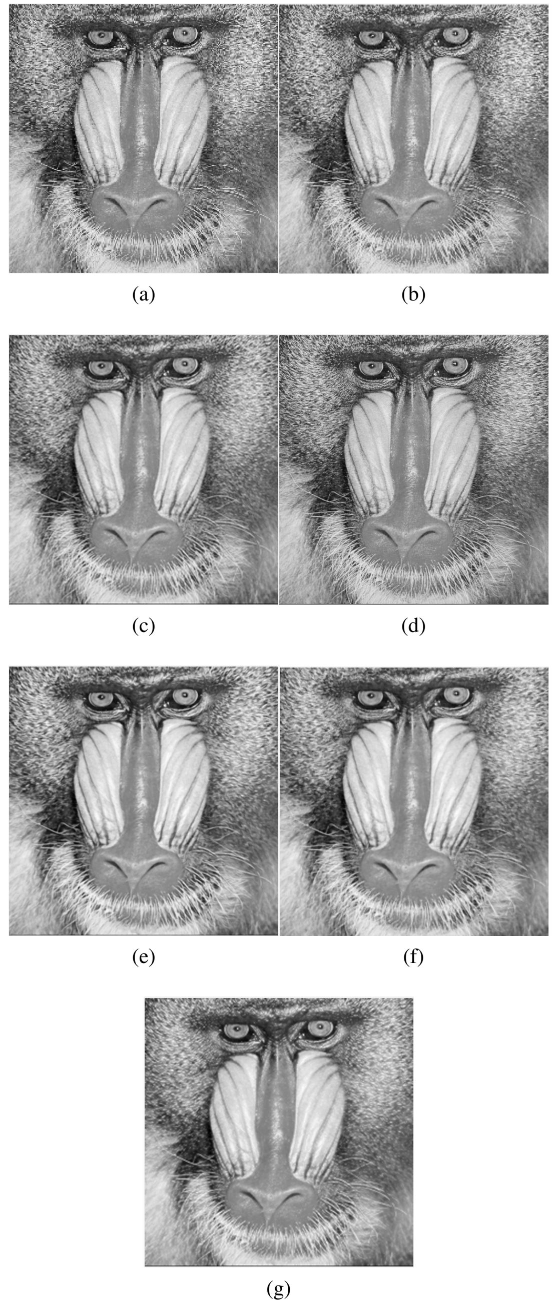
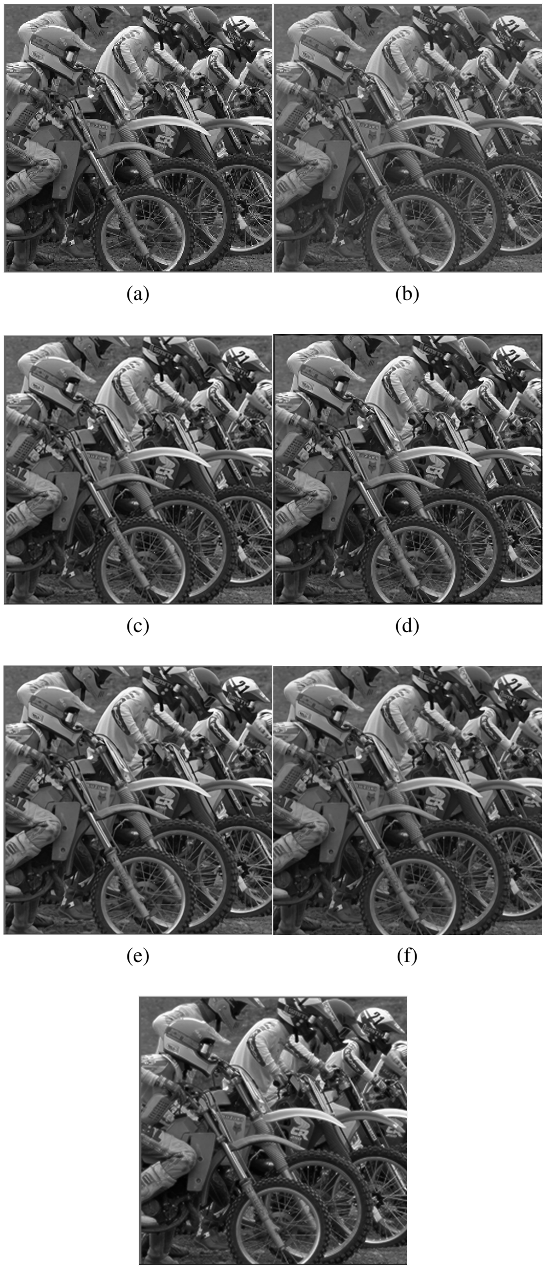


Fig. 2: (a) LR image and results of several up-scaling algorithm at 1:4 up-scaling by (b) Bicubic [2] (c) Lanczos [4] (d) DCC [5] (e) NEDI [6] (f) LMMSE [9] (g) Proposed method.

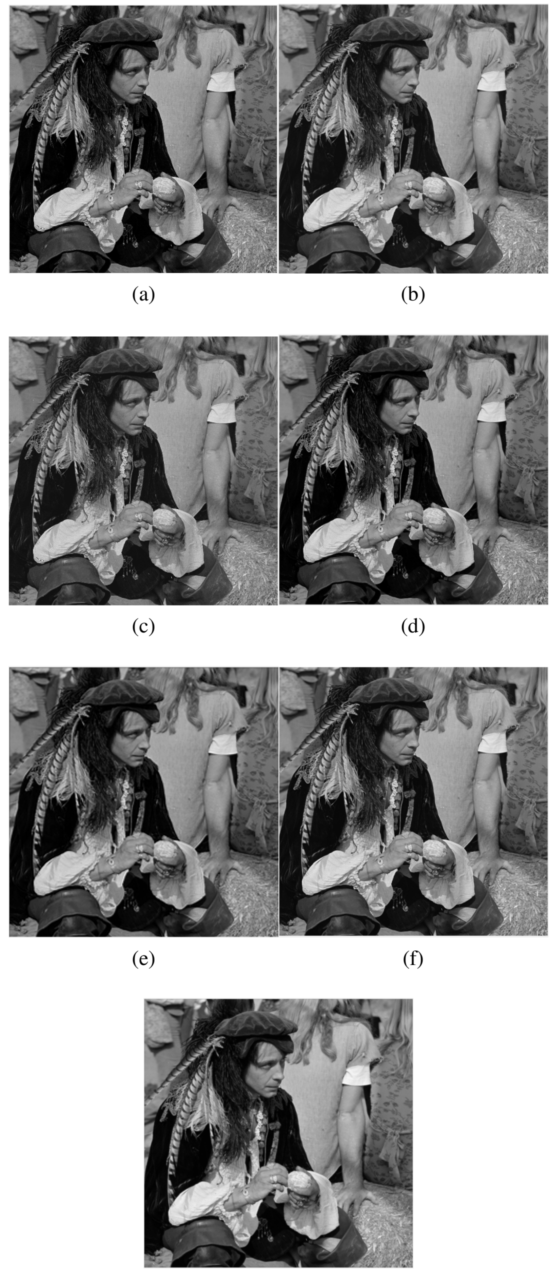
IV. Conclusion

A sophisticated pre-processing method is proposed for reducing the blurring artifacts that arise because of Lanczos interpolation. This blurring causes the degradation in the edge part of image. So to overcome this, one edge-error image is used. The edge-error is obtained by taking a difference in the edge part of LR image and down-sample HR image. Using the concept of unsharp masking, the error is added with an LR image followed by up-sampling. The sharpening of the



(a) (b) (c) (d) (e) (f) (g)

Fig. 3: (a) LR image and results of different up-scaling algorithm at 1:4 up-scaling by (b) Bicubic [2] (c) Lanczos [4] (d) DCC [5] (e) NEDI [6] (f) LMMSE [9] (g) Proposed method.



(a) (b) (c) (d) (e) (f) (g)

Fig. 4: (a) LR image and results of different up-scaling algorithm at 1:16 up-scaling by (b) Bicubic [2] (c) Lanczos [4] (d) DCC [5] (e) NEDI [6] (f) LMMSE [9] (g) Proposed method.

final interpolated HR image depends on k. If its value will be less so, a more sharpened image HR can be obtained. The restored HR image gives the natural looks while preserving all the texture and edge details.

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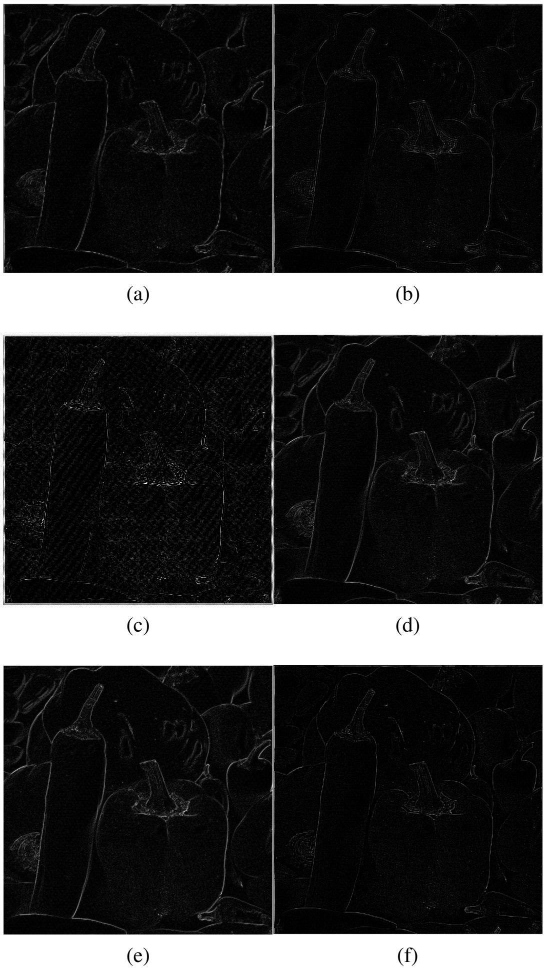

Fig. 5: Error image of various interpolation algorithm at 1:4 up-scaling by (a) method in [2] (b) method in [4] (c) method in [5] (d) method in [6] (e) method in [9] (f) Proposed method.

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