Region Based Laplacian Post-processing for Better 2-D Up-sampling

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***Abstract*—Up-sampling plays an essential role while increasing the resolution of an image or a video intra frame through interpolation. Since the up-sampling process is analogous to a low pass filtering operation, it produces undesirable blurring artifacts that deteriorate the signal quality in terms of loss of fine details and critical edge information. To overcome this problem, a no reference, region adaptive, 2-D Laplacian based post processing technique is proposed here. The proposed method sharpens the Lanczos-3 based up-sampled video intra frame based on its region statistics so as to compensate the high frequency loss. Generally, in an image, the degree of blurring is more in the high variance regions as compared to the regions with low variance. Therefore, to restore the high frequency information, the sharpening should be more in the high variance regions than its low variance counterpart. Hence, in this proposed method, a 2-D Laplacian kernel is made adaptive as per the statistical local variance of a 3×3 neighbourhood. If the local variance is more, the central kernel weight becomes proportionately high and vice versa based on the direct mapping basis. The remaining pixel weights of the Laplacian kernel are adjusted as per the central pixel weight such that the sum of all weights in the adaptive Laplacian kernel is zero. Experimental results reveal that the proposed method outperforms most of the widely used existing interpolation techniques in terms of objective and subjective measures.**

Keywords—image and video processing; Laplacian; up-sampling; interpolation; Lanczos-3 interpolation; local variance

I. INTRODUCTION

In recent times, 2-D up-sampling through interpolation has become one of the promising areas of research worldwide in view of its numerous applications in day to day life. Interpolation now stands as a strong contender in various image and video processing applications because of its potential features like scalability, compatibility and enhanced restored image quality under various constraints. Currently, it is being widely exploited in image and video communication and is providing excellent results. The scalable feature of interpolation makes the video compatible over a wide range of display devices with different resolutions starting from cell phones to HDTV. Furthermore, the exploitation of potential features like adaptability and flexibility of an interpolation technique enables it to provide considerable up-sampling performance under varying constraints such as variation in zooming conditions, change in compression ratio and the video types. Thus, these features of interpolation make the video compatible to various platforms under varying circumstances.

Up-sampling plays a major role in image communication in restoring the high resolution 2-D signals from its low resolution counterpart at the receiver. Generally, at the transmitting end, a video intra frame is sub-sampled to lessen the bandwidth required for transmission. At the receiver, the resolution of the sub sampled intra frame is improved to the original by a suitable interpolation technique. This process not only lessens the signal bandwidth for transmission but also avoids channel congestion through a communication link. In addition, interpolation plays a significant role in various applications such as medical diagnosis, satellite image monitoring, video surveillance and many more. In such applications, it is very often required to improve the native resolution of the original image for proper inspection and recognition. For such operations, interpolation is used as a post processing step so as to improve the native resolution of the captured image for subsequent analysis and interpretation.

In medical image processing, image interpolation methods have taken a vital role for image generation and post-processing. In computed tomography (CT) or magnetic resonance imaging (MRI), image reconstruction requires interpolation to approximate the discrete function to be back projected for inverse Rondon transform. In modern X-ray imaging system such as digital subtraction angiography (DSA), interpolation is used to enable the computer-assisted alignment of the current radiograph and the mask image. Moreover, zooming or rotating medical images after their acquisition often is used in diagnosis and treatment. In order to achieve this, interpolation methods are incorporated into systems for computer aided diagnosis (CAD), computer assisted surgery (CAS), and picture archiving and communication systems (PACS) [1]. Beside this, interpolation is also used in discrete image manipulation, such as geometric alignment and registration to improve the image quality of display devices. Beside this, it plays an important role in the field of lossy image compression wherein some pixels or some frames are discarded during the encoding process and must be regenerated from the remaining information for decoding.

There are several interpolation techniques used for the up-sampling process. One of the simplest interpolation technique is a nearest neighbour interpolation. In this case, the value of a new point in the interpolated image is taken as the value of old coordinate which is located nearest to the new point. Although it is a simple technique, it suffers through blocking artefacts. Another simple interpolation technique is bilinear interpolation where the value of a new point is computed using linear interpolation of four pixels surrounding the new point [2]. Bilinear interpolation though is simple and less complex, it has undesirable blurring artefacts. There are widely used interpolation techniques [3, 6] such as Bicubic and B-spline which consider sixteen pixels for determining a new interpolated point. These techniques provide better performance in terms of quality at the cost of computational complexities. Bicubic and B-spline interpolation techniques provide a less degree of blurring in comparison to bilinear interpolation. Lanczos is another spatial domain interpolation technique which is implemented by multiplying a sinc function with a sinc window which is scaled to be wider and truncated to zero outside of a range [7, 8]. Even if Lanczos interpolation gives good results, it is slower than other approaches and provides a blurring effect in the reconstructed image. Many approaches for image resizing have been developed in transform domain [9, 11]. Up-sampling in DCT domain is implemented by padding zero coefficient to the high frequency side. Image resizing in DCT domain shows very good result in terms of scalability and image quality. However, this technique suffers through undesirable blurring and ringing artefacts. Thus, there is a requirement of an efficient interpolation technique which not only gives a very less amount of blurring with fine details and edge preservation but also improves the subjective and objective quality of an up-sampled video intra frame. The proposed, region adaptive, Laplacian based post processing scheme sharpens the up-sampled intra frame based on its region statistics such that the high variance regions with more high frequency information are sharpened more than the flat regions with less high frequency information. So, the proposed post-processing scheme is based on an inverse modelling approach to counteract the blurring problem in an up-sampled intra frame.

The organization of the paper is structured as follows. The proposed method is described in the subsequent section. Section-3 provides the simulation results of different interpolation algorithms subjected to various constraints. Finally, the work is concluded in section-4.

II. Proposed Method

In the proposed method, a sub-sampled video is produced by alternate deletion of rows and columns at the transmitter for effective transmission channel bandwidth utilization. At the receiver, the resolution of the sub-sampled video is enhanced to its original size by Lanczos-3 interpolation technique. Finally, the Lanczos-3 based up-sampled intra-frame is sharpened as per the region statistics of a 3x3 neighbourhood using the region adaptive Laplacian kernel. This post processing technique is intended for reducing the blurring which arises due to the Lanzos-3 based up-sampling scheme. So, the proposed scheme is based on an inverse modelling approach of high frequency degradation. Thus, the proposed scheme is meant for the restoration of high frequency contents that may be lost while converting a low resolution intra frame to its high resolution counterpart.

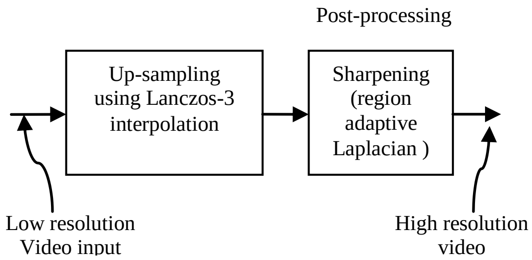


Fig. 1. Region adaptive Laplacian based post processing

Up-sampling using interpolation is analogous to LPF (low pass filter) operation as it shows the similar effects as that of LPF. Therefore, to combat the blurring problems caused by different interpolation techniques, the proposed method makes use of a region adaptive 2-D Laplacian based post processing technique. The proposed scheme sharpens the high variance regions more than the low variance regions using region adaptive 2-D Laplacian kernel. In this case, the central weight of Laplacian kernel is updated as per statistical local variance of a 3×3 neighbourhood on direct mapping basis. The remaining weights of Laplacian kernel are adjusted as per the central weight. Since during up-sampling process, the high frequency regions such as fine details and edges are more deteriorated than the slowly varying smooth regions, the sharpening is made more in the high frequency regions than the regions of low frequency. This aims to nearly equalize the uneven degree of blurring at different regions. In this way, an inverse modeling approach is developed by the proposed method so as to nearly equalize the extent of blurring at different regions by adaptive sharpening.

In addition, the region adaptive Laplacian kernel improves the adaptability of the proposed technique under various constraints such as change in compression ratio, zooming conditions and video types. On this basis, the proposed no reference post processing technique not only enhances the subjective and objective quality of the up-sampled video intra frame but also gives much pronounced edge with very less degree of blurring and fine detail preservation under a variety of circumstances. The proposed method consists of basically 2 steps. They are namely,

- 2-D up-sampling of low resolution video intra frame using the Lanczos-3 interpolation technique.
- Region adaptive Laplacian based post processing.

A. *Up-sampling using Lanczos-3 interpolation*

Lanczos is a spatial domain interpolation technique which is implemented by multiplying a sinc function with a sinc window which is scaled to be wider and truncated to zero outside of the main lobe. In case of Lanczos-3 interpolation, the main lobe of the sinc function along with the two subsequent side lobes on either side is used as a sinc window. The Lanczos window is a product of sinc functions $\sin c(x)$ with the scaled version of the sinc function $\sin c(x/a)$ restricted to the main period $-a \le x \le a$ to form a convolution kernel for re-sampling the input field [7]. In one dimension, the Lanczos interpolation formula is given by,

$$L(x)=\begin{cases}\sin c(x)\sin c(x/a), & -a\le x\le a\\ 0, & otherwise\end{cases} \quad (1)$$

Where 'a' is a positive integer, typically 2 or 3, is used for controlling the size of the kernel. The parameter 'a' corresponds to the number of lobes of the sinc function. The 3 lobed Lanczos windowed sinc function (Lanczos-3) is given by,

$$Lanczos\,3(x)=\begin{cases}\dfrac{\sin(\pi x)}{\pi x}\;\dfrac{\sin(\pi x/3)}{\pi x/3}, & -3\le x\le 3\\ 0, & otherwise\end{cases} \quad (2)$$

For a two dimensional function such as an image $f(x,y)$, an interpolated value at an arbitrary point (x_0, y_0) using Lanczos-3 interpolation is given by

$$\hat{f}(x_0,y_0)=\sum_{i=\lfloor x_0\rfloor-a+1}^{\lfloor x_0\rfloor+a}\;\sum_{j=\lfloor y_0\rfloor-a+1}^{\lfloor y_0\rfloor+a} f(i,j)\,L(x_0-i)\,L(y_0-j) \quad (3)$$

Where $a=3$ for Lanczos-3 kernel which denotes the size of the kernel. The Lanczos-3 interpolation in 2D uses a support region of 6×6=36 pixels from the original image [8].

B. *Region adaptive Laplacian based post processing*

In the final step, the region adaptive Laplacian kernel is used in a post-processing operation to alleviate the blurring in the up-sampled intra-frame. In this proposed method, initially the maximum local variance is calculated within an intra frame. The local variance is then estimated for each pixel in a 3×3 neighbourhood within the intra frame. The estimated local variance is then normalized to 0 to 10 scale by dividing it with the maximum local variance and then by multiplying it with a scaling factor 10. The local variance can also be normalized to 0 to 8 scale or any other values near to 10 such as 4, 7, 9 or 12 etc. It is because these coefficients in this range will nearly approximate the normal operating central weight of a non-adaptive Laplacian kernel. For our convenience, we have mapped the local variance to 0 to 10 scale for improved performance. The remaining weights of the adaptive kernel are adjusted according to the central kernel weight such that the sum of all the weights of the adaptive Laplacian kernel is zero as shown in the equation (4). The region adaptive Laplacian kernel is shown in Fig. 2.

$$\sum_{i=1}^{9} Wt_i = 0 \quad (4)$$

If the statistical local variance of a neighbourhood is more, so does the central weight of the 2-D Laplacian kernel on the direct mapping basis and vice versa. In this way, the weights of the region adaptive Laplacian kernel are updated by local variance so as to perform an adaptive sharpening based on region statistics. This provides the basis for the inverse operation of high frequency degradation and is meant for the restoration of high frequency details.

Now the weighted output of the region adaptive Laplacian is added to the blurred up-sampled intra frame to generate the restored, de-blurred video intra frame. The value of the weight factor K differs for different compression ratio. At 4:1 compression ratio, the weight factor is kept 0.5 whereas at 16:1 compression ratio the value is kept at 2.5. This is because, at lower compression ratio, the blurring is less and therefore the value of K is kept low in order to perform adequately less degree of sharpening. On the other hand, at 16:1 compression ratio, the degree of blurring is more. Therefore, to lessen the high level of blurring, the value of K is kept high.

Algorithm for region adaptive Laplacian

for $n=1$ to frame number do

1. Find the maximum local variance v_{max} for the intra frame.
2. *for* $x=1$ *to number of rows*

   for $y=1$ *to number of columns*

   Find local mean m and local variance v in a neighbourhood.

   $$m \leftarrow \frac{1}{9}\sum_{s=-1}^{1}\sum_{t=-1}^{1} w(x+s, y+t)$$

   $$v \leftarrow \frac{1}{9}\sum_{s=-1}^{1}\sum_{t=-1}^{1} [\hat{f}(x+s, y+t)-m]^2$$
3. Normalize the local variance to 0 to 10 scale

   $$V_N = \frac{10\times v}{v_{max}}$$
4. Form an adaptive 2-D Laplacian kernel using normalized local variance V_N.

   $$h \leftarrow \begin{bmatrix} 0 & -\frac{V_N}{4} & 0\\ -\frac{V_N}{4} & V_N & -\frac{V_N}{4}\\ 0 & -\frac{V_N}{4} & 0\end{bmatrix}$$
5. Find out the convolution between the input intra frame $f(x,y)$ and the region adaptive Laplacian kernel h.

   $$f_1(x,y) \leftarrow \sum_{-1}^{1}\sum_{-1}^{1} h(s,t)\,\hat{f}(x+s\,,\,y+t)$$
6. Obtain the sharpened intra frame $g(x,y)$

   $$g(x,y) \leftarrow \hat{f}(x,y) + K\; f_1(x,y)$$

   where $K=0.5$ *for* $4:1$ *compression ratio*

   $K=2.5$ *for* $16:1$ *compression ratio*

   end for

   end for

end for

$$\begin{array}{|c|c|c|} \hline 0 & -\dfrac{Wt}{4} & 0 \\ \hline -\dfrac{Wt}{4} & Wt & -\dfrac{Wt}{4} \\ \hline 0 & -\dfrac{Wt}{4} & 0 \\ \hline \end{array}$$

Fig. 2. Region adaptive Laplacian kernel for post-processing operation.

III. Experimental Results and Discussion

To demonstrate the performance of the proposed post processing scheme, the input video sequences are down-sampled in the spatial domain by deleting alternate rows and columns at (4:1) and (16:1) compression ratio respectively. Then for each scheme, we interpolate the frames back to their original size to allow the comparison with the original video. Table 1 and Table 2 illustrate the average PSNR comparison of DCT, Bicubic, Lanczos-3 and the proposed post-processing techniques at 4:1 and 16:1 compression ratios respectively. Experimental results reveal, at 4:1 compression ratio the proposed technique shows the average PSNR improvement up to 1.479 dB than DCT and an improvement up to 2.106 dB than the popular Bicubic interpolation technique particularly in the case of ice sequence. Similarly in 16:1 compression ratio, the proposed technique achieves a gain up to 1.013 dB than DCT and an improvement up to 1.398 dB than the popular Bicubic interpolation technique in case of ice sequence. The average PSNR gain at 4:1 compression ratio is more than the gain at 16:1 compression ratio. It is because, at a high compression ratio, most of the high frequency details are lost, finally giving a flat and blurred output. Since the proposed method employs the high frequency details of the up-sampled intra frame for sharpening it, the PSNR gain is less at a higher compression ratio than the low compression counterpart. In Fig. 3 and Fig. 4 the variations of PSNR w.r.t the frame index are shown at 4:1 and 16:1 compression ratio respectively. In either case, the proposed method yields better PSNR gain than the other widely used interpolation techniques for different types of sequences. The subjective performance of the proposed technique is illustrated in Fig. 5 and Fig. 6 for the 33rd frame of akiyo and 5th frame of football sequence respectively at 4:1 compression ratio. Experimental results show, the blurring is much reduced and the edges are more pronounced with fine detail preservation in comparison to other existing interpolation techniques.

TABLE I. Average PSNR Comparison of Different Sequences at 4:1 Compression Ratio

Video sequences	**Average PSNR (dB)**			
	Bicubic	***Lanczos-3***	***DCT***	***Proposed***
Ice	80.728	81.278	81.355	**82.384**
Football	76.702	77.501	77.823	**78.395**
Xylophone	78.518	79.008	79.147	**80.019**
Akiyo	81.050	81.589	81.788	**82.526**
City	75.724	76.012	75.984	**76.369**
Container	73.693	74.135	74.383	**74.702**
Mobile	69.328	69.727	69.889	**70.412**
Soccer	78.386	78.797	78.881	**79.225**
Stefan	70.855	71.135	71.148	**71.462**
Coastguard	74.632	75.071	75.213	**75.445**
Flower	67.445	67.632	67.619	**67.921**
Hallmonitor	74.858	75.272	75.717	**76.688**
Foreman	79.764	80.215	80.567	**80.644**
Salesman	77.110	77.457	77.571	**77.910**
Tennis	73.365	73.560	73.584	**74.188**
Bus	73.393	73.847	73.925	**74.412**
News	76.465	77.088	77.293	**77.947**
Lab	75.788	76.117	76.384	**76.533**
IR	78.251	78.665	78.705	**79.050**
Highway	85.705	86.391	86.595	**86.847**

TABLE II. Average PSNR Comparison of Different Sequences at 16:1 Compression Ratio

Video sequences	**Average PSNR (dB)**			
	Bicubic	***Lanczos-3***	***DCT***	***Proposed***
Ice	75.542	75.845	75.927	**76.940**
Football	71.322	71.517	71.636	**71.908**
Xylophone	73.660	73.846	73.941	**74.382**
Akiyo	76.214	76.411	76.448	**76.951**
City	72.371	72.468	72.451	**72.561**
Container	69.664	69.755	69.735	**69.854**
Mobile	65.834	65.930	65.921	**66.157**
Soccer	74.261	74.448	74.482	**75.606**
Stefan	67.665	67.774	67.847	**67.737**
Coastguard	70.656	70.757	70.768	**70.519**
Flower	64.966	65.032	65.045	**65.139**
Hallmonitor	70.794	70.958	71.013	**71.211**
Foreman	74.865	75.101	75.566	**75.607**
Salesman	73.268	73.398	73.398	**73.527**
Tennis	70.864	70.905	70.874	**71.331**
Bus	69.083	69.187	69.157	**69.084**
News	70.751	70.970	70.946	**71.145**
Lab	72.132	72.221	72.413	**72.651**
IR	73.438	73.689	73.772	**74.070**
Highway	78.445	78.834	78.946	**79.341**

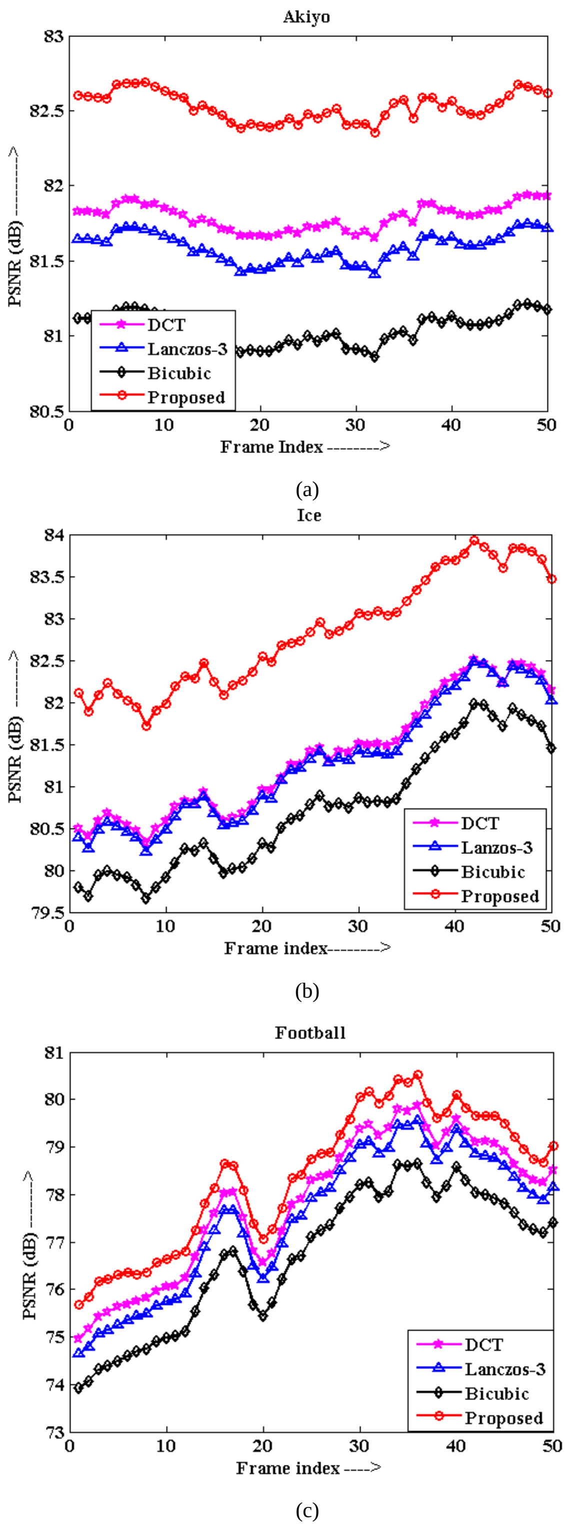


Fig. 3. PSNR (dB) comparison of different interpolation techniques for various video sequences at 4:1 compression ratio: (a) akiyo; (b) ice ; (c) football.

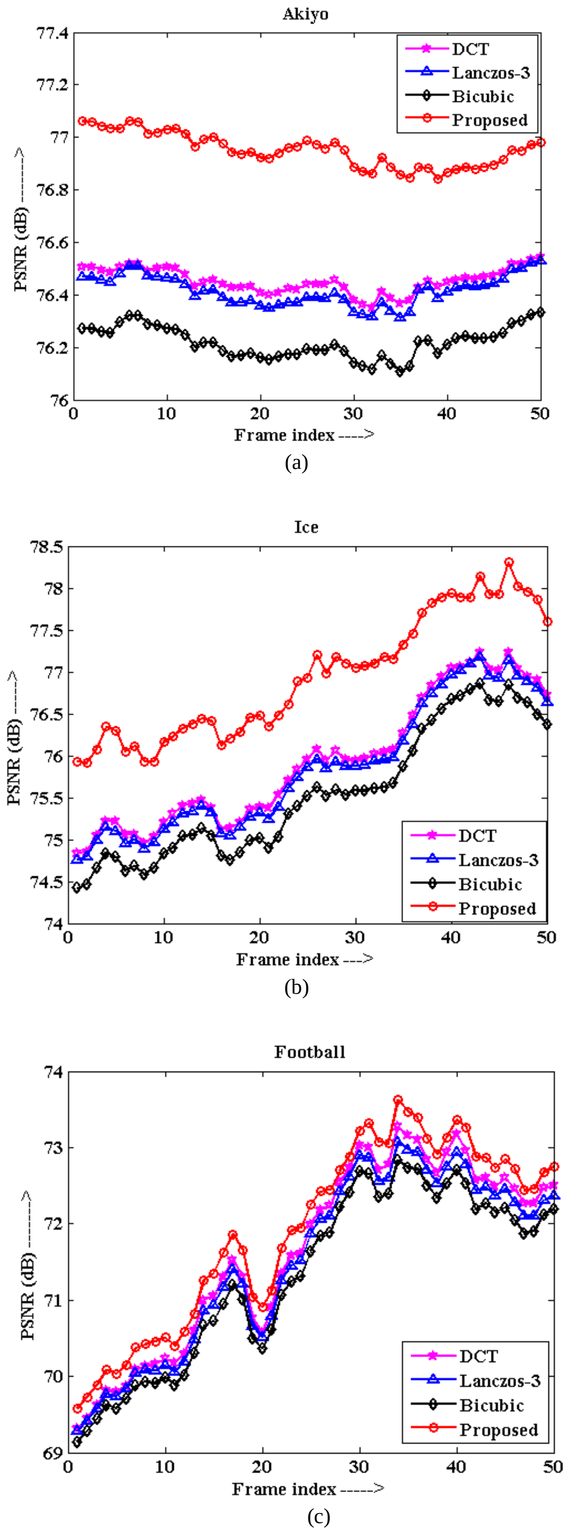
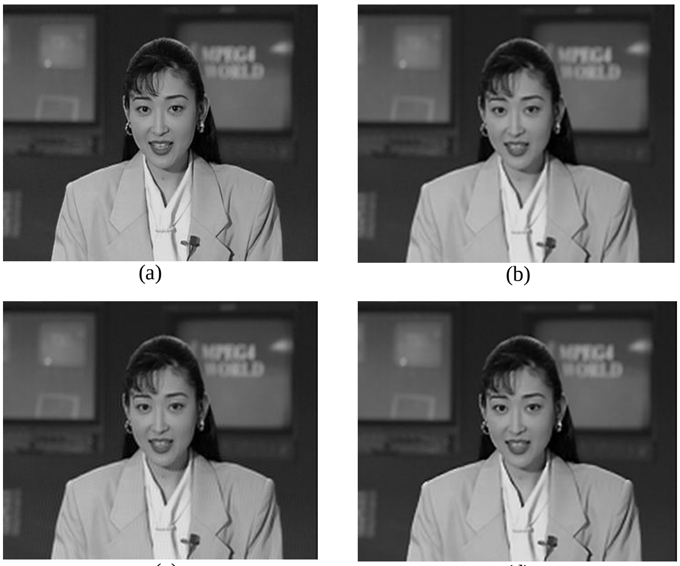
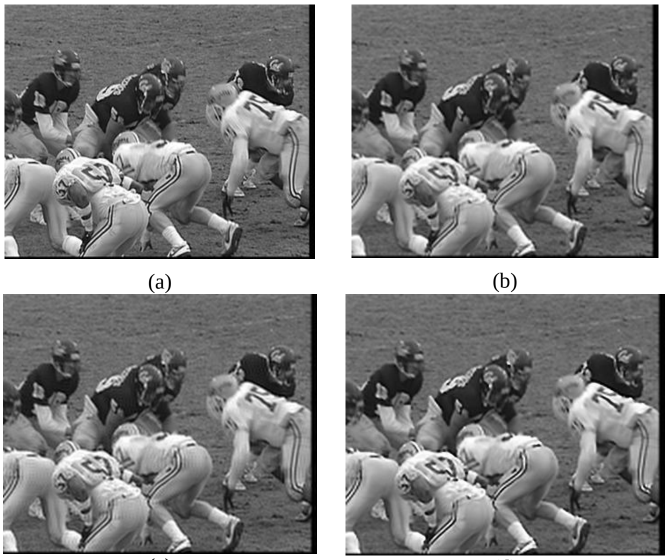


Fig. 4. PSNR (dB) comparison of different interpolation techniques for various video sequences at 16:1 compression ratio: (a) akiyo; (b) ice ; (c) football.



(a) (b) (c) (d)

Fig. 5. Subjective performance of 33rd frame of akiyo sequence at 4:1 compression ratio using various interpolation techniques: (a) Original; (b) Lanczos-3; (c) DCT; (d) Proposed.



(a) (b) (c) (d)

Fig. 6. Subjective performance of 5th frame of football sequence at 4:1 compression ratio using various interpolation techniques: (a) Original; (b) Lanczos-3; (c) DCT; (d) Proposed.

IV. CONCLUSION

The proposed post-processing scheme is based on an inverse modelling approach for high frequency degradation which restores the fine details and edge information i.e. lost during the up-sampling process. In addition, this alleviates the problem of nonlinear blurring caused by the up-sampling operation. The qualitative and quantitative improvement of the proposed technique is gained due to the region statistics based direct mapping technique which updates the adaptive Laplacian kernel weights as per the statistical local variance in a 3×3 neighbourhood. Furthermore, this post-processing scheme not only restores a sub-sampled video with high precision but also yields a very low degree of blurring with fine detail preservation. In addition, the proposed scheme is highly adaptive under various constraints such as change in compression ratio, zooming conditions and the video types. The objective and subjective quality improvement of the proposed technique can be notified in terms of significant improvement in PSNR gain, much pronounced edge, less degree of blurring and fine details preservation under a variety of circumstances.

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