No Reference, Fuzzy Weighted Unsharp Masking Based DCT Interpolation for Better 2-D Up-sampling

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***Abstract*—Up-sampling plays a crucial 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. In order to resolve this problem, a no reference, fuzzy weighted unsharp masking based DCT interpolation technique is proposed here. The proposed method is an anticipatory, spatial domain, fuzzy logic based preprocessing approach which sharpens the sub-sampled or low resolution video intra frames depending on their region statistics in order to compensate the blurring caused by the subsequent DCT interpolation technique. According to this method, the regions with high variance are sharpened more than the regions with low variance based on the Fuzzy rule base. This consequently results in the restoration of fine details and edge information in the reconstructed up-sampled video intra frame with improved objective and subjective quality.**

Keywords—unsharp masking; discrete cosine transform; interpolation; fuzzy logic; local variance

I. INTRODUCTION

Recently 2-D interpolation has become the most promising area of research and has drawn the attention of many researchers worldwide. It is now widely exploited in contemporary image and video communication and is providing excellent results because of its potential features like scalability, compatibility and restored image quality. This scalable feature of interpolation makes the video compatible over a wide range of display devices with different resolutions such as cell phones, digital TV and HDTV etc. In addition, it plays a key role in reducing the transmission bandwidth requirement of a video signal and thereby avoids channel congestion.

Up-sampled high resolution video not only gives a better visual quality to a viewer but also provides additional information for various post processing applications such as inspection or recognition. In medical imaging, satellite remote sensing and video surveillance applications, very often it is desired to improve the native resolution offered by imaging hardware for subsequent analysis and interpretation. Video interpolation aims to generate high resolution video from the associated low resolution capture and hence is very essential for the above mentioned applications.

Scalability is one of the key features of video interpolation which is widely used in internet technology and consumer electronics applications. For instance, while remote browsing a video database, it would be more convenient and economical to send a low resolution version of a video clip to the user. If the user shows interest the resolution can be progressively enhanced using interpolation. Similarly HDTV exploits the scalable feature of video interpolation for its compatibility with most of the existing video compression standards such as H.263 and H.264. In addition, the video is made adaptive to variable bit rate and computational capacities of different receiving devices by utilizing the scalable feature of interpolation. Thus the analysis and exploitation of 2-D interpolation are quite essential to improve the performance of contemporary image and video communication in terms of quality, scalability and compatibility.

There are several interpolation techniques are used for re-sampling process. One of the simplest interpolation technique is bilinear interpolation where the value of a new point is computed using linear interpolation of four pixels surrounding the new point [1]. Bilinear interpolation though is simple and less complex, it has undesirable blurring artifacts. There are widely used interpolation techniques such as Bicubic and B-spline [2] 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 [3]. 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. 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 artifacts [4]. Several hybrid interpolation techniques have been developed in order to reduce the blurring artifacts. However they do have certain limitations. The adaptive unsharp masking based sharpening is a spatial domain pre-processing approach which extracts high frequency details in the spatial domain, sharpens the sub-sampled video to a certain degree through an adaptive selection of weight factor by referring the original frame after a regular interval so as to compensate the blurring caused by the subsequent discrete DCT based interpolation technique. The main drawback of this technique is the requirement of the corresponding original frame after a regular frame interval [5]. There are so many no reference hybrid interpolation techniques which are giving better results. No reference, region adaptive unsharp masking based interpolation techniques [6], [7] though provide good results, they lack in several aspects. Since these techniques are developed using a crisp rule, they are unable to adapt with varying constraints and thereby unable to provide better performance for different types of images and video sequences. In case of video sequences subjected to zoom in or zoom out conditions, these techniques fail drastically. Their performance also deteriorates if subjected to variation in compression ratio and video characteristics. It is because, there are only few output values for a large variation in the input values so the problems lies in the in-proper mapping between input and output values using crisp rule base. This problem can be resolved by using the proposed fuzzy based mapping technique in which there will be as a de-fuzzified crisp output value corresponding to each crisp input value which may vary over a large range. Thus there is a precise and accurate mapping between input and output by using fuzzy inference system. Furthermore, this consequently improves the adaptability of the proposed fuzzy based technique with the varying conditions. Therefore, the proposed technique aims to produce very less degree of blurring and at the same time flexible enough to provide considerable performance under varying constraints such as compression ratio, video characteristics and zooming conditions.

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

Generally at the transmitting end, an image or a video intra frame is sub-sampled by alternate deletion of rows and columns in order to save the bandwidth required to transmit the signal. At the receiver, the sub-sampled video intra frame is restored to its original size by using a suitable interpolation technique. In a communication system, the 2-D signal sub-sampling and up-sampling process can be modelled as a low pass filtering operation which results in loss of high frequency information of an image such as fine details and edge information. However, the low frequency information such as smooth and slowly varying region details are retained due to such operations. For instance, a DCT based up-sampling scheme has an important property of preserving the low frequency components generated by smooth and fast changing

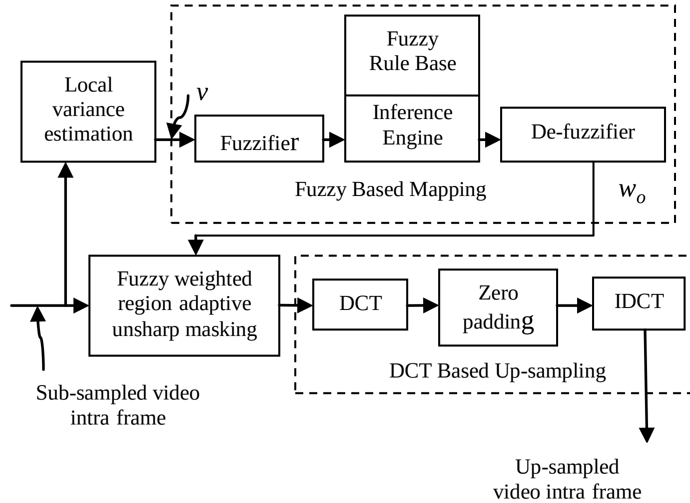


Fig. 1. Block diagram of the proposed fuzzy weighted, region adaptive unsharp masking based DCT interpolation technique.

area in a video intra frame because of its similarity with the low pass filtering (LPF) operation. Thus, in an image or video intra frame, the high frequency details are more degraded than the low frequency details. Keeping this thing in view, an efficient, hybrid interpolation technique is proposed here which will perform the inverse operation so as to restore the high frequency details more than low frequency details based on fuzzy rule base. Thus, the proposed method utilizes a preprocessing, fuzzy based, region adaptive unsharp masking technique which sharpens the video intra frame locally as per the statistical local variance so as to alleviate the blurring caused by 2-D sub-sampling and up-sampling operation. As per the fuzzy knowledge base, the region with higher variance are sharpened more than the region with lower variance so as to perform the inverse operation of high frequency degradation caused by 2-D sub-sampling and up-sampling process. It is due to the precise and accurate mapping between input and output variable of the fuzzy inference system, the proposed system is made adaptive to varying constraints such as zooming conditions, compression ratios and video characteristics. In addition, to restore the high frequency details, the proposed sharpening technique is performed prior to the DCT based up-sampling such that a precise amount of sharpening will compensate the degree of blurring caused by the subsequent DCT based interpolation technique. Consequently, this results in reduced blurring in the up-sampled video intra frame with better visual quality.

The proposed method comprises of basically four basic steps.

1) Local variance estimation .
2) Fuzzy based mapping.
3) Fuzzy weighted region adaptive unshap masking.
4) DCT based up-sampling.

A. Local Variance Estimation

Local variance is the measure of high frequency details in a neighborhood of an intra frame. Since the proposed method is a region based technique, the local variance is calculated at each pixel of an intra frame in order to show the level of high frequency details in a neighborhood. The local variance is used as the input variable to the Fuzzy inference system which generates a defuzzified crisp output as an adaptive central weight of the Gaussian mask based on Fuzzy rule base. This technique will be fully explained in the subsequent step. Let m and v represent the local mean and local variance of a 3×3 neighborhood of an intra frame $f(x, y)$ respectively. The local variance v is given by

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

$$v = \frac{1}{9}\sum_{s=-1}^{1}\sum_{t=-1}^{1}[f(x+s, y+t) - m]^2 \tag{2}$$

B. Fuzzy based Mapping

Fuzzy based techniques are designed to handle various nonlinear problems. The blurring caused by the up-sampling operation is nonlinear since more blurring takes place in the high variance regions than the low variance regions. In order to resolve this nonlinear problem of nonuniform blurring, fuzzy based mapping technique is used which maps the central weight of the Gaussian mask w with respect to the local variance v as per the fuzzy rule base. v and w are denoted as input and output variable of the fuzzy inference system respectively.

Fuzzy logic controllers are governed by a set of if-then rule known as a knowledge base or rule base. The fuzzy rule base drives the inference engine to produce the output in response to one or a set of inputs. The inputs are in general real world analog signals are termed as crisp input. These inputs are converted to fuzzy variable in fuzzifier. The fuzzifier inputs are sent to the inference engine to generate a controller response in fuzzy environment with the help of the fuzzy rule base. The inference engine operates with various fuzzy based operators such as min-max or product–max etc. These responses are then defuzzified to real world analog signal in the De-fuzzifier [8].

The fuzzy logic controller maps a crisp input to a crisp output through four blocks. The fuizzifier changes the crisp input based on membership function into fuzzy values or fuzzy sets. These fuzzy values are mapped in the inference engine to another set which is derived from the knowledge base. The knowledge base consists of rules provided by an expert or even obtained from numerical data. These rules are expressed as a set of "if-then" explicitly defining the nature of control action to be achieved for a certain input or a set of inputs. These rules decide the quality of the control action. The inference engine assigns a weight to the rule based on inputs, implications and aggregation operators. This caters to the quantitative nature of the control action. Hence the designing of fuzzy logic controller for a specific application deals with

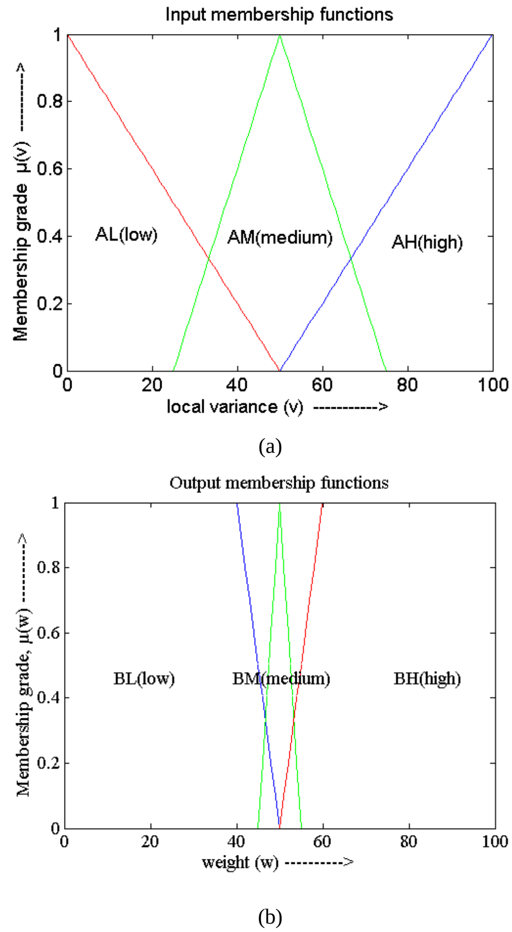


Fig. 2. Plot of (a) input membership functions; (b) output membership functions

- Deciding the membership function for fuzzifier and De-fuzzifier.
- Deciding the input and output ranges based on heuristic knowledge.
- Creation of knowledge base established on expert operator strategies.
- Deciding the inference operator or the De-fuzzification method.

Deciding the membership function plays an important role in solving a specific problem. In this method, the triangular membership function is selected for input variable while a combination of triangular and trapezoidal membership function is taken for output to combat the nonuniform blurring problem. This is a single input single output fuzzy system where the input (local variance) is normalized to (0-100) scale while the output variable w range is set within 0 to 100 based on heuristic knowledge. The expressions for input and output membership functions are given by

$$\mu_{AL}(v;\, 0,\, 0,\, 50) = \begin{cases} 0, & v \le 0 \\ \dfrac{50-v}{50}, & 0 \le v \le 50 \\ 0, & 50 \le v \end{cases} \quad (3a)$$

$$\mu_{AM}(v;\, 25,\, 50,\, 75) = \begin{cases} 0, & v \le 25 \\ \dfrac{v-25}{50-25}, & 25 \le v \le 50 \\ \dfrac{75-v}{75-50}, & 50 \le v \le 75 \\ 0, & 75 \le v \end{cases} \quad (3b)$$

$$\mu_{AH}(v;\, 50, 100, 100) = \begin{cases} 0, & v \le 50 \\ \dfrac{v-50}{100-50}, & 50 \le v \le 100 \\ 0, & 100 \le v \end{cases} \quad (3c)$$

Where $\mu_{AL}(v)$, $\mu_{AM}(v)$ and $\mu_{AH}(v)$ denote the low, medium and high membership function for the input variable respectively. Similarly the low, medium and high membership function of the output variable are denoted by $\mu_{BL}(w)$, $\mu_{BM}(w)$ and $\mu_{BH}(w)$ respectively. Input and output membership functions are shown in Fig. 2. The input variable is represented as the local variance, v. Similarly the output variable is represented as the central weight of the adaptive Gaussian mask, w. The expressions for output membership function are given by

$$\mu_{BL}(w;\, 0,\, 0,\, 40,\, 50) = \begin{cases} 1, & 0 \le w \le 40 \\ \dfrac{50-w}{50-40}, & 40 \le w \le 50 \\ 0, & w \ge 50 \end{cases} \quad (4a)$$

$$\mu_{BM}(w;\, 45,\, 50,\, 55) = \begin{cases} 0, & w \le 45 \\ \dfrac{w-45}{50-45}, & 45 \le w \le 50 \\ \dfrac{55-w}{55-50}, & 50 \le w \le 55 \\ 0, & 55 \le w \end{cases} \quad (4b)$$

$$\mu_{BH}(w;\, 50,\, 60,\, 100,\, 100) = \begin{cases} 0, & w \le 50 \\ \dfrac{w-50}{60-50}, & 50 \le w \le 60 \\ 1, & 60 \le w \le 100 \end{cases} \quad (4c)$$

Fuzzy logic controllers are governed by a set of if-then rule known as a knowledge base or rule base. The fuzzy rule base drives the inference engine to produce the output in response to one or a set of inputs. The knowledge base established on a heuristic approach is given as follows.

FUZZY IF – THEN RULES :

RULE I : if local variance (v) is low then weight (w) is high

OR

RULE II : if local variance is medium then weight is medium

OR

RULE III : if local variance is high then weight is low

The rule base contains all the information required to relate the inputs and outputs. In this case, the independent variables of the membership functions of input and output are different, so the result will be two dimensional. Hence the minimum of the input and the output membership function is performed as per the fuzzy if-then rules. Subsequently, the inference engine operates with the min - max operator to generate the output responses. The output responses are then de-fuzzified to produce a crisp output using the center of gravity method. Now the minimum of the two membership function is given by

$$\mu_{AL\cap BH}(v,w) = \min\{\, \mu_{AL}(v)\, ,\, \mu_{BH}(w)\, \} \quad (5a)$$

$$\mu_{AM\cap BM}(v,w) = \min\{\, \mu_{AM}(v)\, ,\, \mu_{BM}(w)\, \} \quad (5b)$$

$$\mu_{AH\cap BL}(v,w) = \min\{\, \mu_{AH}(v)\, ,\, \mu_{BL}(w)\, \} \quad (5c)$$

Now to determine the output weight w_o for a specific input v_o, AND operation is performed between $\mu_{AL}(v_o)$ and the general result $\mu_{AL\cap BH}(v,w)$ evaluated at v_o according to fuzzy if-then rule-1. Let it be $Q_1(w)$. Similarly $Q_2(w)$ an $Q_3(w)$ are calculated for rule-2 and rule-3 respectively.

$$Q_1(w) = \min\{\, \mu_{AL}(v_o)\, ,\, \mu_{AL\cap BH}(v_o\, ,\, w)\, \} \quad (6a)$$

$$Q_2(w) = \min\{\, \mu_{AM}(v_o)\, ,\, \mu_{AM\cap BM}(v_o\, ,\, w)\, \} \quad (6b)$$

$$Q_3(w) = \min\{\, \mu_{AH}(v_o)\, ,\, \mu_{AH\cap BL}(v_o\, ,\, w)\, \} \quad (6c)$$

In order to obtain the overall response, the individual responses are aggregated by OR operation. Thus the overall response $Q(w)$ is given by

$$Q(w) = Q_1(w)\, \cup\, Q_2(w)\, \cup\, Q_3(w) \quad (7)$$

$$\Rightarrow\quad Q(w) = \max\, \{\, Q_1(w)\, ,\, \max\, \{\, Q_2(w)\, ,\, Q_3(w)\, \}\, \} \quad (8)$$

The crisp output w_o from the fuzzy set Q is obtained by center of gravity de-fuzzification method. Since $Q(w)$ can have K possible values, $Q(1), Q(2), \ldots Q(K)$, its center of gravity is given by

$$w_o = \frac{\sum_{w=1}^{K} w\,Q(w)}{\sum_{w=1}^{K} Q(w)} \quad (9)$$

Now, the de-fuzzified crisp output w_o is used to update the central weight of the Gaussian mask for the subsequent region adaptive unsharp masking operation.

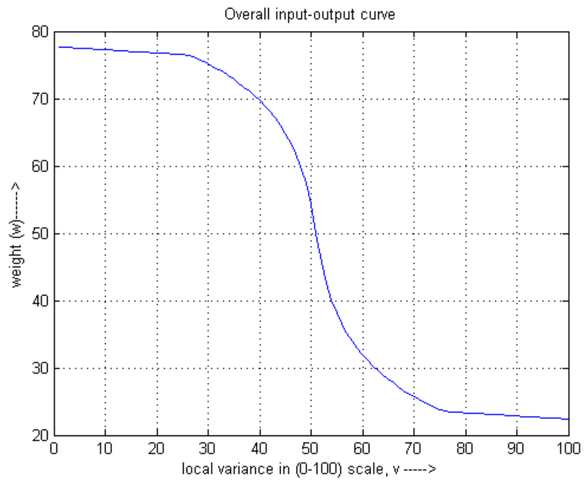


Fig. 3. Overall input-output curve between local variance (v) and central weight (w) of 11th frame of football sequence.

$$\frac{1}{12+w_o}\times\begin{array}{|c|c|c|}\hline 1 & 2 & 1\\ \hline 2 & w_o & 2\\ \hline 1 & 2 & 1\\ \hline\end{array}$$

Fig. 4. Fuzzy weighted, region adaptive Gaussian mask.

C. Fuzzy Weighed Region Adaptive Unsharp Masking

The Fuzzy weighted, region adaptive unsharp masking operation is used to sharpen a video intra frame by subtracting the unsharp or smoothed version of it from the original. The smooth version of a video intra frame is obtained by blurring it using a Fuzzy weighted region adaptive Gaussian mask whose central weight is varied depending on the statistical local variance of a neighborhood. The central weight is updated by the de-fuzzyfied crisp output w_o. As per the fuzzy rule base, the central weight of Gaussian mask will be more if the local variance is less and vice versa. This results in proportionately low degree of blurring in low variance region and high degree of blurring in the high variance regions. Subsequently, the blurred video intra frame is subtracted from the original to produce the unsharp mask. Further, by adding the unsharp mask to the original, a sharpened video frame is obtained [9] in which the regions with higher local variance are sharpened more than the regions with lower local variance in order to compensate the blurring caused by the subsequent DCT based interpolation technique. Thus the proposed technique lessens the blurring effect by DCT interpolation and improves the PSNR (dB) gain of the reconstructed video intra frame.

In brief, the Fuzzy weighted region adaptive unsharp masking consists of the following steps.

- Determination of local variance of an intra frame as input variable.
- Fuzzy based mapping between local variance v and central weight of the Gaussian mask w_o by using the knowledge base.
- Central weight updation of the Gaussian mask by the de-fuzzyfied crisp output w_o.
- The original video frame is blurred by using the fuzzy weighted region adaptive Gaussian mask.
- The blurred video frame is subtracted from the original. The resulting difference is called as the unsharp mask.
- The unsharp mask is then added to the original to generate the sharpened video intra frame and this operation is repeated for all the frames.

Let, $f(x,y,n)$ denote the blurred video sequence and the original video sequence respectively. Therefore, The fuzzy weighted, region adaptive unsharp mask is given by

$$g_{mask}(x,y,n)=f(x,y,n)-g_1(x,y,n) \tag{10}$$

$g_1(x,y,n)$ is obtained by using the fuzzy weighted, region adaptive blurring technique. The unsharp mask is then added back to the original video intra frame to generate the sharpened sequence and is given by

$$g_2(x,y,n)=f(x,y,n)+g_{mask}(x,y,n) \tag{11}$$

Where $g_2(x,y,n)$ denotes the sharpened video sequence. n represents the frame number that represents discrete time. The fuzzy weighted, region adaptive Gaussian mask is given in Fig. 4. In this figure, w_o represents the center pixel weight of the mask which is made adaptive as per the statistical local variance of a 3×3 neighborhood.

D. DCT Based Up-sampling

To implement up-sampling in DCT domain, we need to add N zeros in the high frequency regions, where N is the signal length. Subsequently, type-II $IDCT$ of the extended $2N$ samples is performed to obtain the two-fold up-sampled data. This process was described at length in [6]. In the case of 2-D video intra frames, the twofold up-sampling process in a matrix form can be described as

$$b^U_{2N\times 2N}=W^T_{2N\times 2N}\times\begin{pmatrix}2W_{N\times N}b_{N\times N}W^T_{N\times N} & 0\\ 0 & 0\end{pmatrix}\times W_{2N\times 2N} \tag{12}$$

Where W denotes the 1-D type-II DCT kernel. b and b^U are the down-sized and the up-sampled frame block. 0 denotes a $N\times N$ zero matrix [4].

III. Experimental Results and Discussion

To demonstrate the performance of the proposed hybrid technique, 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 frame.

TABLE I. AVERAGE PSNR COMPARISON OF DIFFERENT CIF SEQUENCE AT 4:1 COMPRESSION RATIO.

Sequence	Average PSNR (dB)			
	Bicubic	***Lanczos-3***	***DCT***	***Proposed***
football	76.698	77.497	77.817	78.224
news	76..464	77.088	77.293	77.583
Bus	73.393	73.847	73.925	74.146
akiyo	81.042	81.581	81.778	81.981
mobile	69.328	69.727	69.888	70.110
coastguard	74.631	75.069	75.211	75.422
hallmonitor	74.858	75.272	75.717	75.910
container	73.698	74.139	74.387	74.585
Salesman	77.110	77.457	77.570	77.744
laboratory	75.788	76.117	76.383	76.511
city	75.722	76.010	75.982	76.087
Stefan	70.864	71.144	71.156	71.265
flower	67.444	67.632	67.619	67.704
foreman	79.764	80.215	80.567	80.645
tennis	73.364	73.560	73.584	73.656
soccer	78.384	78.795	78.879	78.977

TABLE II. AVERAGE PSNR COMPARISON OF DIFFERENT CIF SEQUENCES AT 16:1 COMPRESSION RATIO

Sequence	Average PSNR (dB)			
	Bicubic	***Lanczos-3***	***DCT***	***Proposed***
football	71.3216	71.5169	71.6358	71.7182
news	70.7512	70.9707	70.9456	71.0367
bus	69.0830	69.1872	69.1570	69.1996
akiyo	76.2144	76.4112	76.4478	76.5070
mobile	65.8343	65.9303	65.9213	65.9590
coastguard	70.6563	70.7569	70.7682	70.7511
hallmonitor	70.7940	70.9583	71.0127	71.0309
container	69.6644	69.7546	69.7354	69.7354
Salesman	73.2679	73.3983	73.3981	73.4548
laboratory	72.1371	72.2209	72.4130	72.4514
city	72.3711	72.4679	72.4509	72.4673
Stefan	67.6652	67.7742	67.8474	67.8985
flower	64.9665	65.0323	65.0454	65.0719
foreman	74.8651	75.1006	75.5657	75.6025
tennis	70.8640	70.9054	70.8735	70.8582
soccer	74.2612	74.4484	74.4829	74.4849

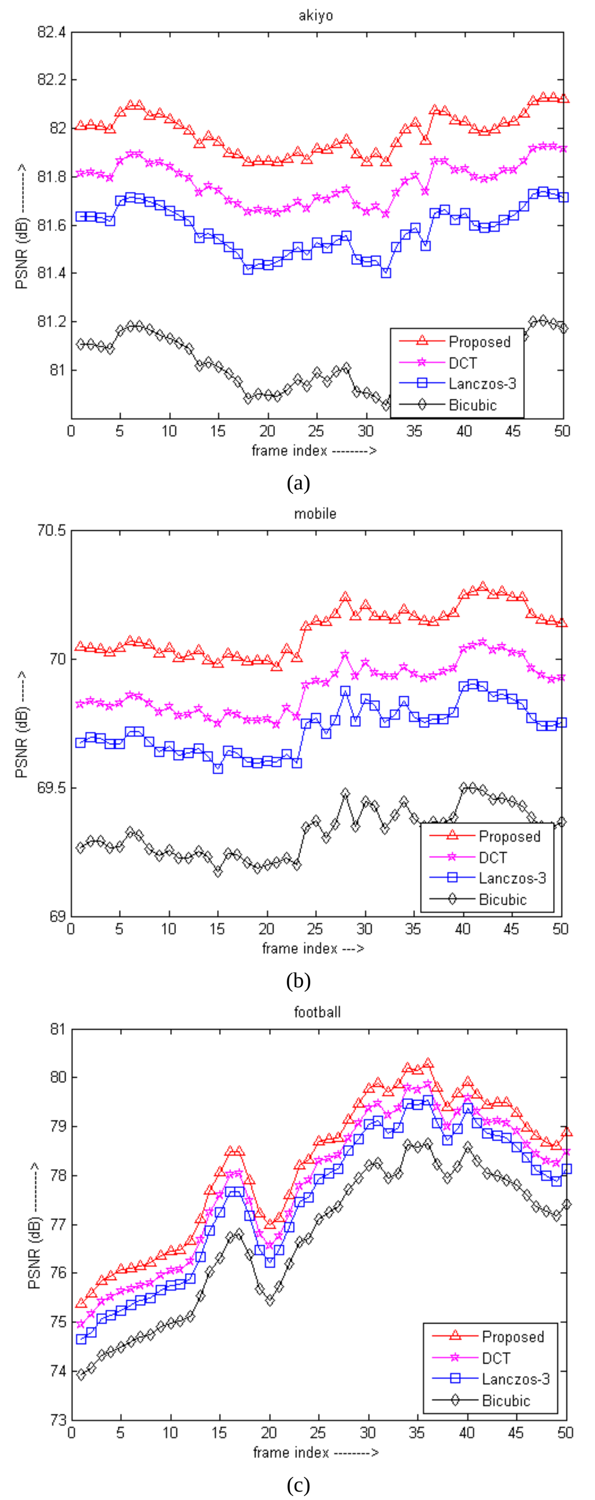
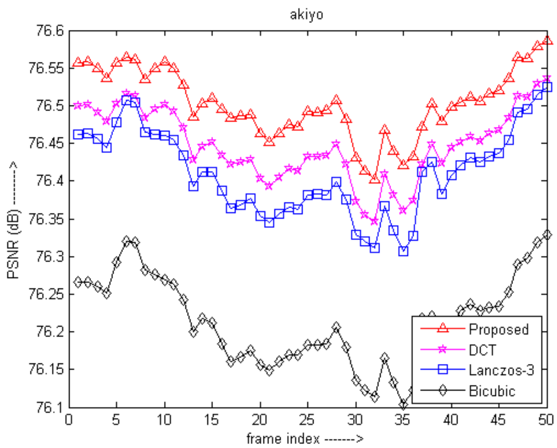
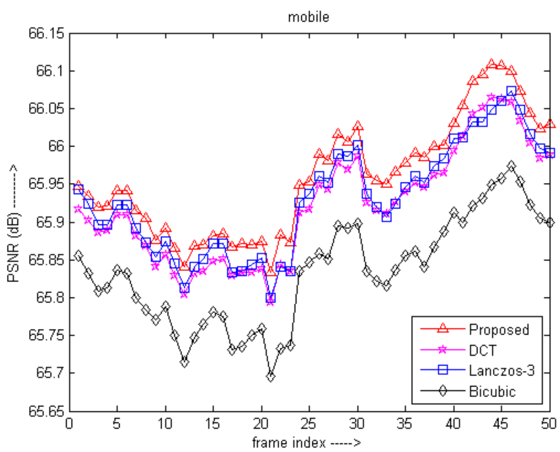


Fig. 5. PSNR (dB) comparison of different interpolation techniques for various video sequences at 4:1 compression ratio: (a) akiyo; (b) mobile; (c) football.

Table 1 and Table 2 illustrate the average PSNR comparison of DCT, Bicubic, Lanczos-3 and the proposed interpolation 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

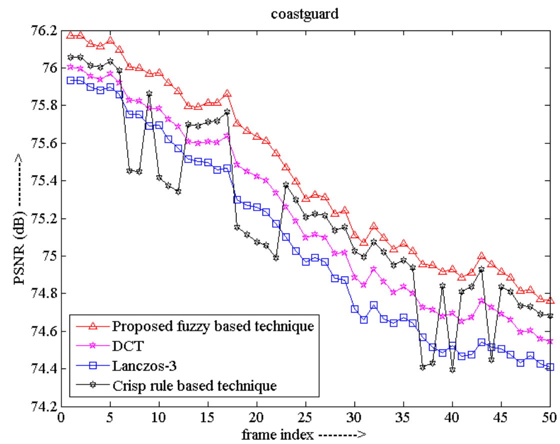


(a)

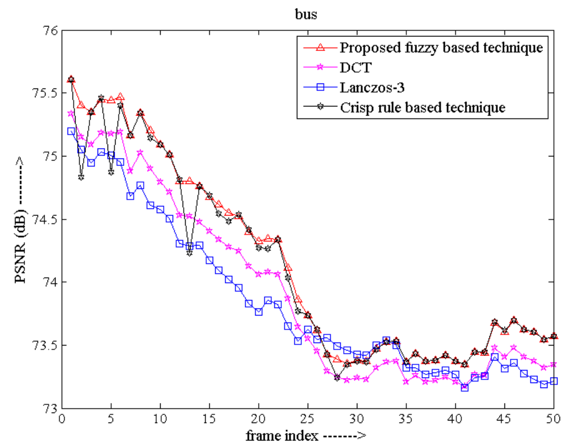


(b)

Fig. 6. PSNR (dB) comparison of different interpolation techniques for various video sequences at 16:1 compression ratio: (a) akiyo; (b) mobile.



(a)



(b)

Fig. 7. Performance comparison between the proposed fuzzy based technique and the crisp rule based technique under varying zooming conditions at 4:1 compression ratio: (a) coastguard; (b) bus.

to 0.407 dB than DCT and an improvement up to 1.526 dB than the popular Bicubic interpolation technique particularly in the case of football sequence. Similarly the proposed technique achieves a gain up to 0.091 dB than DCT at 16:1 compression ratio in case of news 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 sub-sampled intra frame for sharpening it so as to reduce the blurring caused by the subsequent DCT interpolation, the PSNR gain is less at a higher compression ratio than the low compression counterpart. In Fig. 5 and Fig. 6 the variations of PSNR w.r.t the frame index are shown at 4:1 and 16:1 compression ratio respectively. In either of the case, the proposed method yields better PSNR gains than the other widely used interpolation techniques for different types of sequences.

In Fig. 7, the performance comparison between the proposed fuzzy based technique and the crisp rule weighted unsharp masking based DCT interpolation [7] is shown under varying zooming conditions. Experimental results reveal that the crisp rule weighted technique is inconsistent in providing better results than DCT under the variation in zooming conditions. Although, the crisp rule based method gives better performance in some of the frames, due to lack of adaptability, the performance deteriorates for the remaining frames. This problem is due to improper mapping between input and output variable. In the crisp rule based method, a wide range range of input values is mapped to only few (six) output values. This leads to loss of intermediate values to map the exact output value as required. On the other hand, in the proposed method, a wide variation in the input values is mapped to as many numbers of output values based on fuzzy rule base. Thus, there is an accurate and precise mapping between input and output which not only provide better performance but also makes the proposed method adaptive to varying constraints such as zooming conditions, compression ratio and the video characteristics. The subjective performances of different interpolation techniques are illustrated in Fig. 8 for the 33rd frame of akiyo sequences 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 irrespective of the video types.

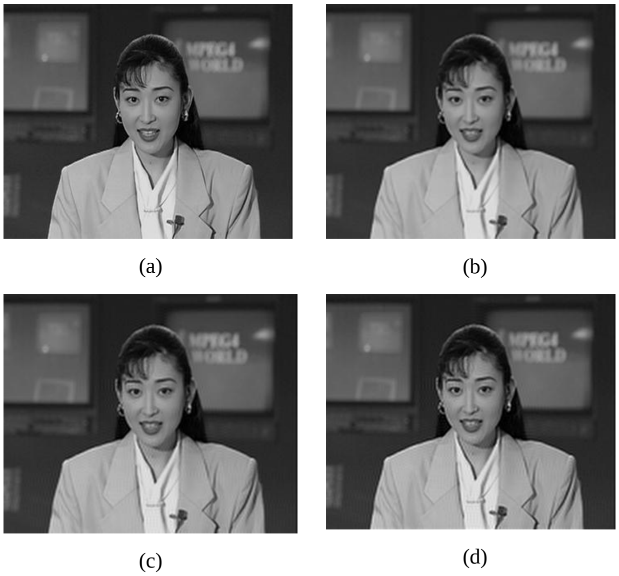


Fig. 8. Subjective performance of 33rd frame of akiyo sequence at 4:1 compression ratio using various interpolation techniques: (a) Original; (b) Lanczos-3; (c) DCT; (d) Proposed.

IV. CONCLUSION

In this paper, a no reference hybrid interpolation technique is proposed which not only restores a sub-sampled video with high precision but also yields a very low degree of blurring with fine detail preservation. It delivers superior performance and high degree of flexibility under a variety of constraints such as change in compression ratio and the video types. It achieves better performance of video reconstruction by exploiting the advantages of spatial domain fuzzy weighted, region adaptive unsharp masking and frequency domain DCT interpolation. The incorporation of fuzzy based preprocessing technique makes the method highly adaptive to varying constraints and hence it works fine with different types of video subjected to change in compression ratio. In addition, by making use of fuzzy based mapping in between local variance and central weight of the Gaussian mask, the proposed method gives much better performance under the change in zooming conditions and thus achieves better subjective and objective performance. Since the proposed method is based on a preprocessing approach, it imparts more computational burden on the transmitting side than the receiving end and thus makes the receiver computationally less complex, fast and suitable for various real time applications. Thus the proposed method is a low complex, highly flexible and efficient technique that works fine with different types of video data.

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