A Low Complex Context Adaptive Image Interpolation Algorithm For Real-Time Applications

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***Abstract*—Recently a lot of interpolation algorithms are proposed, but these interpolation algorithms are highly computationally expensive. Hence these algorithms cannot be implemented and used in real time applications. In view of real time applications we have proposed a computationally simple interpolation algorithm. In our proposed algorithm the unknown pixels are categorized into various bins depending upon the characteristic of the neighboring pixels (activity level) and for each bin fixed prediction parameters are used for prediction. We have presented different set of fixed predictors for both smooth type and edgy type of images. We have also proposed a modified algorithm in which selection of prediction parameter is done on block by block basis instead of image basis. Our proposed algorithm gives much better qualitative and quantitative performance as compared to other computationally simple interpolation algorithms.**
Keywords: Interpolation, Fixed predictors, Switching, Slope, Bin.

I. Introduction

Image Interpolation has a wider range of applications in the field of image processing. It enables the user to generate an image of high resolution from its given low resolution image interactively. Besides its applications in remote sensing, image interpolation is applied in diverse areas ranging from computer graphics, rendering, editing and medical image construction to outline image viewing.

Several good classical interpolation techniques such as bilinear,bicubic,spline are well known now a days and are used in many real time application. However, these methods don't preserve the spatial details of the source image which leads to annoying artifacts like blurring texture, zig-zagging etc. in the interpolated images. In case of bilinear interpolation method, equal weightage has been given to four neighboring pixels without studying the characteristics of neighboring pixels. Hence, bilinear interpolation is not able to preserve the edge information. While in our proposed algorithm we have assigned more weightage to highly correlated pixels and less weightage to remaining neighbouring pixels.

In order to preserve the data related to edge structure, various interpolation algorithms have been developed so far. All these Edge Preserving algorithms are highly complex as it requires estimation of covariance matrix. Li and Orchard [4] suggested the edge directed interpolation algorithm, in which the missing pixels are interpolated based on the estimated covariance of the High Resolution (HR) image from the covariance of Low Resolution (LR) image (NEDI). Jaiswal and Jakhetiya [5] have suggested an algorithm based on down-sampling of image and then using least square (LS) estimation to interpolate it, which consumes high computational power.

The main contribution behind this work is to develop a very low complex image interpolation technique which can be implemented and used in real time applications with better objective and subjective quality as compared to other low complex interpolation algorithm in literature. Like [3], the unknown pixels are divided into several bins depending upon the characteristics of the neighboring pixels. But instead of finding Least Square Based predictor for each bin, we define a fixed set of prediction co-efficient for prediction of unknown pixels. We have proposed different set of prediction parameters for both edgy and smooth images. Thus using these fixed set of predictors do not requires any least squares estimation which results into less consumption of computational power.

Remaining part of the paper is organized as follows. Section II discuss the review of existing algorithm [3]. Section III discusses proposed image dependent and image independent algorithm. Simulation results and concluding remarks are made in section IV and V respectively.

II. Review of Context Based Interpolation (CBI)

A context based switching interpolation algorithm [3] was designed in which unknown pixels are divided into several classes depending on the characteristics of neighboring pixels. All the unknown pixels of HR image are interpolated in two phases.

A. Phase-I

It categorize all the unknown pixels into a particular bin as shown in Table I, on the basis of characteristics of their neighboring pixels (activity level) as shown in Fig.1(a) where slope bin values S_D ($d_{45} - d_{135}$) are calculated, where $d_{45} = |G-C| + |C-B| + |B-F|$ and $d_{135} = |E-A| + |A-D|$ $+|D-H|$. It is expected that unknown pixels of each bin will show similar characteristics.

Thus a fourth ordered LS based predictors (α_1, α_2, α_3, and α_4) is calculated to interpolate the unknown pixels belonging to each bin using (1).

$$X(n) = \alpha_1 A + \alpha_2 B + \alpha_3 C + \alpha_4 D \tag{1}$$

978-1-4577-1772-7/12/$26.00

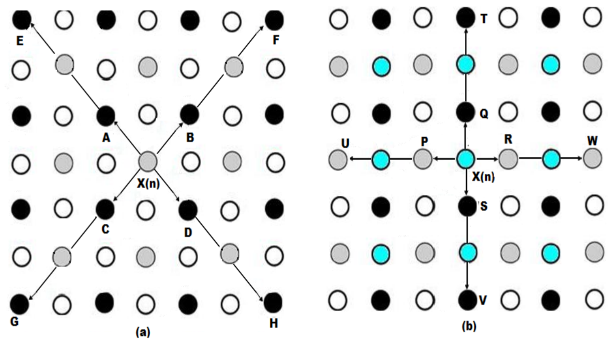

Fig. 1. Neighboring pixels (Context) used for obtaining characteristics (activity level) for interpolation in (a) First Phase and (b) Second Phase.

B. Phase-II (Interpolation of rest of the pixels)

In second phase, remaining pixels are categorized into eight bins on the basis of the characteristics of their neighboring pixels as shown in Fig.1(b) whereas bin values S_H $(d_H - d_V)$ are calculated, where $d_H = |U - P| + |P - R| + |R - W|$ and $d_V = |V - S| + |S - Q| + |Q - T|$. And it find fourth ordered LS based parameters (β_1, β_2, β_3, and β_4) for each bin to interpolate the missing pixels.

Hence, in order to interpolate all unknown pixels, CBI [3] requires 16 fourth ordered LS based parameters. Estimation of LS based predictor requires a lot of multiplication and matrix inversion which is significantly more computationally complex as compared to other conventional simple interpolation algorithm discussed in literature.

III. Proposed Algorithm

In this paper, we propose a less complex context based switching interpolation algorithm. We follow the same procedure of CBI [3] while categorizing the unknown pixels into several classes. For each class of unknown pixels, fixed prediction coefficients are used for prediction. We have proposed two different interpolation algorithms in which different set of fixed prediction parameters are defined for both edgy and smooth type of blocks or images.

A. Context Based Image Dependent (CBID) Interpolation

In this algorithm, we interpolate the missing pixels of the HR image in two phases as done in CBI:

1) Phase-1: All the unknown pixels in this phase are divided in 8 bins on the basis of slope value S_D as shown in Table I. Since the unknown pixels in a particular bin are expected to show similar characteristics, we assigned a fixed prediction coefficient for pixels belonging to each bin depending on the characteristics of the input images (Edgy or Smooth type). The prediction coefficients corresponding to each bin for smooth image (variation among pixels are less) as well as for edgy type of images (variation among pixels are more) is shown in Table II and III respectively.

Thus depending on the characteristic of the image, all unknown pixels of Phase 1 are predicted using (2) with the help of prediction coefficients (α_1, α_2, α_3, and α_4) given in Table II and Table III.

TABLE I
Classification of slope bins.

Input S	Bin	Description
$S \geq 40$	Bin 1	Sharp edge along angle 135
$40 > S \geq 20$	Bin 2	Edge along 135
$20 > S \geq 8$	Bin 3	Weak edge along angle 135
$8 > S \geq 0$	Bin 4	No edge
$0 > S \geq -8$	Bin 5	No edge
$-8 > S \geq -20$	Bin 6	Weak Edge along 45
$-20 > S \geq -40$	Bin 7	edge along angle 45
$S \geq -40$	Bin 8	Sharp edge along angle 45

TABLE II
Prediction Coefficients for First phase (α_1, α_2, α_3, and α_4) and Second phase (β_1, β_2, β_3, and β_4) for smooth images

Bin	α_1	α_2	α_3	α_4	β_1	β_2	β_3	β_4
Bin 1	.315	.178	.181	.327	.348	.150	.352	.152
Bin 2	.229	.254	.269	.246	.219	.285	.219	.276
Bin 3	.288	.212	.215	.284	.310	.185	.312	.193
Bin 4	.257	.241	.237	.261	.124	.317	.232	.326
Bin 5	.224	.278	.279	.209	.197	.301	.193	.308
Bin 6	.241	.257	.252	.248	.232	.270	.236	.262
Bin 7	.194	.301	.307	.198	.172	.305	.218	.303
Bin 8	.153	.355	.345	.148	.231	.270	.231	.269

$$X(n) = \alpha_1 A + \alpha_2 B + \alpha_3 C + \alpha_4 D \tag{2}$$

2) Phase-2 : The interpolation of the missing pixels in second phase is almost of same kind. In this phase also rest of the pixels will be distributed among 8 bins, but for the distribution of pixels we need the slope value which is calculated with different neighboring pixels than that of phase-1 (as shown in Fig.1(b)). In this phase, slope (S_H) is calculated and similar bin boundary values of CBI [3] are used.

As unknown pixels in the same bin are expected to show similar characteristics. Thus these unknown pixels are predicted by (3) with the help of fixed proposed prediction coefficient (β_1, β_2, β_3, and β_4) shown in Table II and III depending upon the type of image (edgy or smooth).

$$X(n) = \beta_1 P + \beta_2 Q + \beta_3 R + \beta_4 S \tag{3}$$

Thus the proposed CBID can be summarized as follows:

1) Identify the type of LR image (Smooth or Edgy).
2) If it is smooth, then use prediction co-efficient (α_1, α_2, α_3, and α_4) from Table II in first phase and (β_1, β_2, β_3, and β_4) for second phase respectively. Else prediction co-efficients from table III will be used in the same way.

The criteria of deciding an image to be smooth or edgy is explained as follows:

We have calculated the slope value (activity level) in first phase which depends upon the characteristics of the neighboring pixels. It can be observed from Table I that pixels belonging to $Bin1$ and $Bin8$ are edgy in nature. Thus, we apply the switching criteria, as when number of pixels in these two bins crosses a predefined threshold, then it is assumed

TABLE III
PREDICTION COEFFICIENTS FOR FIRST PHASE (α_1, α_2, α_3, AND α_4) AND SECOND PHASE (β_1, β_2, β_3, AND β_4) FOR EDGY IMAGES.

Bin	α_1	α_2	α_3	α_4	β_1	β_2	β_3	β_4
Bin 1	.279	.206	.197	.315	.275	.232	.272	.255
Bin 2	.311	.176	.227	.279	.268	.193	.322	.221
Bin 3	.288	.217	.239	.256	.259	.214	.273	.256
Bin 4	.267	.232	.262	.241	-0.02	.295	.378	.338
Bin 5	.290	.198	.228	.283	.243	.279	.237	.245
Bin 6	.271	.257	.239	.233	.295	.189	.253	.262
Bin 7	.286	.224	.232	.255	-0.02	.292	.341	.387
Bin 8	.245	.252	.258	.237	.225	, .276	.218	.281

that the input image is of edgy nature. Thus, in such case, predefined predictors which are given in Table III will be used for prediction of missing pixels in both phases. On the other hand, for images whose number of pixels in $Bin1$ and $Bin8$ do not cross the predefined threshold are assumed to be of smooth type and predictors of Table II will be used to interpolate all the missing pixels in both phases.

Above described proposed algorithm is image dependent where switching of the proposed fixed parameters are made on the study of global characteristics of image. The fixed predictors (Table II and III) for each bin are found as follows:

We classify our image data set [6] into smooth image set and edgy image set. We then found LS based predictor of each slope bin for both the set of images and the obtained parameters are stored. These parameters are applied to their corresponding set of images and PSNR obtained for each set of parameters are noted down. Based on the analysis of PSNR values, fixed predictors are chosen for each set of images.

B. Context Based Image Independent (CBII) Interpolation

Assumption made in proposed CBID algorithm that whole image shows same kind of nature (i.e edgy or smooth) is not true for every image. In this algorithm,we study the local characteristics of an image on block by block basis. We proposed (CBII) algorithm which incorporates the switching of Set 1 (Table II) parameters and Set 2 (Table III) parameters on block by block (non-overlapping blocks) basis instead of image based. The criteria of switching is based on the percentage of edges in the block of pixels. The proposed CBII interpolation algorithm works as follows:

1) It calculates percentage of edges in a block of a low resolution image.
2) If Percentage of edges is greater than a predefined threshold then that implies the block is edgy in nature.
3) Then all the unknown pixels of the corresponding block in the HR image will be interpolated by using prediction co-efficient of Table III.
4) Else the block is smooth in nature and prediction co-efficient of Table II will be used to predict the unknown pixels of the corresponding block in HR image.
5) The threshold estimation is shown in the pseudo code of Fig.2 .

```
Pseudo Code

i ----> input block of size 16*16.

// Scharr Operator
j = [1 2 1 ; 0 0 0 ; -1 -2 -1]

// Convolution of i & j
        k = conv2 ( i , j)

m ----> no. of rows in k.
n  ----> no. of columns in k.

# Scanning all elements of k,
        for q = 1 to m
            for w = 1 to n

                if  abs( k( q, w) ) > 128
                        v++;
                 end

            end
        end
Therefore, % of edge = (v * 100) / (m * n)
```

Fig. 2. Pseudo Code Explaining estimation of percentage of edge in a block

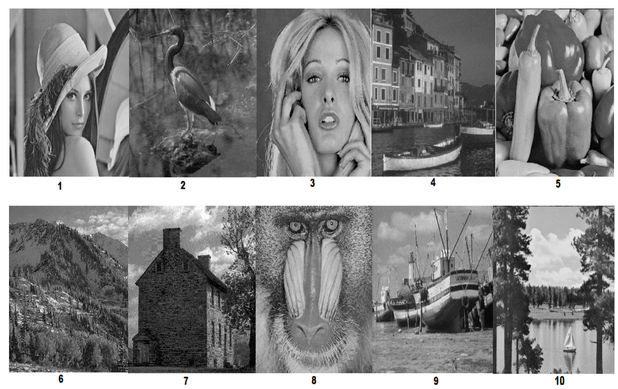

Fig. 3. Test Images of size 512×512

IV. SIMULATION RESULTS

In order to evaluate the performance of the proposed new image interpolation technique, we have conducted extensive experiments in comparison with three other image interpolation techniques: Bicubic interpolation, content adaptive interpolation [2], and bilinear interpolation techniques. Results for Bilinear and Bicubic interpolation methods have been obtained using matlab code in [7]. PSNR of the five different methods are tabulated in Table IV which were applied on the ten test images [6] given in Fig.3. Our proposed algorithm

TABLE IV
PSNR COMPARISON OF INTERPOLATED IMAGES BY DIFFERENT METHODS.

Images	Bicubic [1]	Bilinear	CAI [2]	CBID	CBII
1	31.695	32.96	33.182	33.184	**33.194**
2	31.994	32.768	32.689	32.827	**32.842**
3	28.489	28.193	28.188	28.503	**29.762**
4	30.245	30.308	30.463	30.376	**30.522**
5	30.796	30.088	31.121	31.932	**32.695**
6	21.727	21.875	21.287	21.881	**21.948**
7	22.523	22.871	22.279	22.861	**22.917**
8	22.723	22.616	22.238	22.614	**23.141**
9	28.521	28.19	28.851	28.948	**28.983**
10	29.263	28.672	28.716	29.269	**29.685**
Avg	27.798	27.854	27.901	28.239	**28.569**

TABLE V
AVG PSNR COMPARISON OF ALL 49 INTERPOLATED TEST IMAGES[6] BY DIFFERENT METHODS.

Images	Bicubic [1]	Bilinear	CAI [2]	CBID	CBII
AVG	27.423	27.559	27.358	27.605	**27.768**

TABLE VI
CORRELATION COEFFICIENT OF THE HR IMAGES USING THE MENTIONED INTERPOLATION ALGORITHMS

Images	Bicubic [1]	Bilinear	CAI [2]	CBID	CBII
1	0.9904	0.9929	0.9932	0.9932	**0.9933**
2	0.9715	0.9758	0.9754	0.9762	**0.9765**
3	0.9737	0.9722	0.9718	0.9718	**0.9809**
4	0.9817	0.9820	0.9825	0.9822	**0.9830**
5	0.9907	0.9890	0.9913	0.9928	**0.9941**
6	0.8862	0.8878	0.8747	0.8880	**0.8911**
7	0.9541	0.9575	0.9519	0.9574	**0.9584**
8	0.8995	0.8950	0.8872	0.8950	**0.9087**
9	0.9791	0.9805	0.9804	0.9809	**0.9813**
10	0.9905	0.9891	0.9892	0.9905	**0.9915**
Avg	0.9617	0.9621	0.9597	0.9628	**0.9659**

on an average gives 0.209, 0.345 and 0.410 db better PSNR than Bilinear, Bicubic and CAI [2] respectively. We have also compared the quality of enlarged images produced by these three methods and compared the same with both of our proposed algorithm. It can be seen from Fig.8, that proposed algorithm preserves edges in a better way as compared to other methods.

V. CONCLUSION

This paper presents a computationally simple interpolation algorithm which can be implemented and used in real time applications. We have proposed two different interpolation algorithm where CBID makes prediction using global characteristics of images and CBII uses the local characteristics of images. Both the proposed algorithms follow the same procedure of classifying the unknown pixels into several bins as in CBI [3] but we define a fixed set of prediction parameters for interpolation of unknown pixels for both smooth and edgy blocks/images. By extensive simulation experiments it is found that the proposed algorithms yield a better objective and subjective quality than computationally simple interpolation algorithm with marginal increment in computational cost.

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Fig. 4. Interpolated Image of size 512×512 by Bilinear

Fig. 5. Interpolated Image of size 512×512 by Bicubic[1]

Fig. 6. Interpolated Image of size 512×512 by CAI[2]

Fig. 7. Interpolated Image of size 512×512 by CBID

Fig. 8. Interpolated Image of size 512×512 by CBII

Fig. 9. Original Image of size 512×512