

# An Efficient Image Interpolation Algorithm Based upon the Switching and Self Learned Characteristics for Natural Images

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**Abstract**—This paper presents a new image interpolation technique for enhancement of spatial resolution of images. The proposed algorithm uses the switching of existing Soft-decision Adaptive Interpolation (SAI) algorithm and Single Pass Interpolation Algorithm (SPIA) methods. We learn the error pattern in the interpolation process of SAI method and SPIA Method after interpolating downsampled version of LR image. Then we devised a mechanism to correct the error pattern. Emperically we found that SAI methods works better on smooth images (variation among the pixels is less) while SPIA method works better on detailed images (more variation among the pixels), because of the type of pixels used in the interpolation. So, a hybrid scheme of combining SAI method and SPIA method is proposed for best prediction of high resolution (HR) image. The proposed algorithm produces the best results in different varieties of images in terms of both PSNR measurement and subjective visual quality.

**Index Terms**—Image Interpolation, Switching, Self-Learned Characteristics, Low Resolution Image, Error Energy .

## I. INTRODUCTION

Image interpolation addresses the problem of generating a high-resolution image from its given low-resolution image. Image interpolation is required for multi resolution pyramidal coding, improved definition television receiver design, still photograph zooming and other more general needs for image resolution enhancement. Image interpolation is beneficial and in some cases even necessary in computer vision, surveillance, medical imaging, remote sensing, and other fields.

Conventional interpolation algorithms (e.g nearest neighbor, bilinear, bicubic [2], [5].) based on the image invariant models fail to adapt rapidly varying pixel structures near the edges in the image. However, these interpolation algorithms are generally preferred due to their low computational complexity.

A key requirement for any interpolation algorithm is to preserve the edges in the interpolated image. The traditional bilinear interpolation algorithms [2], [5], are not able to preserve the edges. To preserve edge structures in interpolation, Li and Orchard proposed to estimate the covariance of high-resolution (HR) image from the covariance of the low-resolution (LR) image, and then interpolate the missing pixels based on the estimated covariance (NEDI) [1]. Alternatively, Zhang and Wu proposed to interpolate a missing pixel in multiple directions,

and then fuse the directional interpolation results by minimum mean square-error estimation [3]. Zhang and Wu proposed an Image Interpolation algorithm based on the Adaptive 2-D Autoregressive Modeling and Soft-Decision Estimation (SAI) [4]. Jakhetiya and Tiwari proposed a single pass interpolation algorithm (SPIA) [6] based on least square estimation.

The main contribution of the paper is as follows. We studied the perfomance of SAI and SPIA and found that SAI works better on smooth images while SPIA works well at detail images. After having learned the perfomance of these two algorithm, we proposed to take adavantage of these two algorithms to get a better interpolation algorithms. Basically we learn the error pattern in the interpolation process and then device a mechanism to correct the same. The proposed algorithm first down samples the given LR image and then reconstructs two different LR images from the down-sampled-version of the LR image. This reconstruction is done using SAI and SPIA. Since the original LR and the interpolated LR images are available, the error patterns in possible values of the unknown pixels can be estimated. The learning of error pattern is named as self-learned characteristics (SLC). Interpolation of LR image is done by switching of SAI and SPIA methods on a block by block basis. The criteria of switching is decided by SLC and a threshold (obtained using SLC). The proposed algorithm achieves superior image interpolation results to those reported in the literature.

Rest of the paper is structured as follows. Section 2 discusses the existing methods such as Soft-decision Adaptive Interpolation (SAI) [4] and Single pass interpolation algorithm (SPIA) [6]. In Section 3, we present a new approach of interpolation process i.e, our proposed self-learned characteristics based switched image interpolation algorithm (SLCSI). Experimental Results are included in section 4 and concluding remarks are made in Section 5.

## II. REVIEW OF SAI AND SPIA METHODS

### A. Soft-decision Adaptive Interpolation ( SAI ) algorithm

The SAI algorithm learns and adapts to varying scene structure using a 2-D piecewise autoregressive model. The model parameters are estimated in a moving window in the

input low resolution image. The pixel structure dictated by the learn model is enforced by the soft decision estimation process onto a block of pixels, including both observed and estimation. The SAI method is a two pass process because it uses both known and interpolated pixels to estimate the unknown pixels. So, SAI method propagate error from first pass to second pass. For example, if error in the first pass is

$$error_{firstpass} = \sum_{(m,n)} |Y(2i, 2j) - \hat{Y}(2i, 2j)| \quad (1)$$

Where  $\hat{Y}$  is an interpolated image in the first pass. SAI method gives better prediction quality of the interpolated image for smooth images because error in the first pass is significantly low but in case of detailed images error in first pass is not low which results into much incrementation in error in the second pass.

### B. Single Pass Interpolation Algorithm (SPIA)

Single Pass Interpolation algorithm is a Least squares based interpolation method. SPIA divides the unknown pixels into three different categories and these unknown pixels are predicted using different predictor structures (pixels used for it's interpolation) and different order (number of pixels used in interpolation). SPIA is a block based interpolation method that requires three LS based predictors per block and the predictors are of the order 4 and 6 as shown in fig 1. In this algorithm, the unknown pixels are estimated using the 2-D autoregressive modeling.

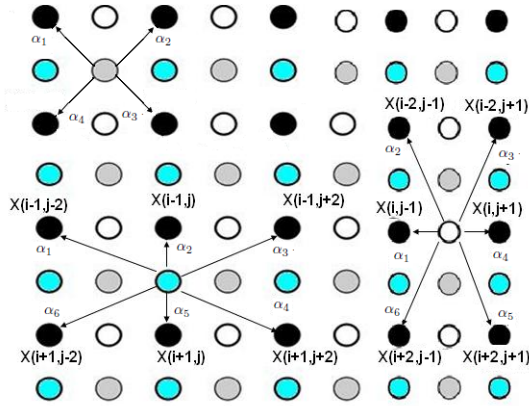


Fig. 1. Formation of HR image and pixel categorization in SPIA

SPIA uses only original pixels to interpolate the unknown pixels. So there is no incrementation of error which was obtained after first pass. Hence SPIA works better on edgy images than other multiple pass algorithms.

### III. PROPOSED ALGORITHM

In the proposed algorithm, we learn the error pattern in the interpolation process and then device a mechanism to correct the same. The process of learning the error pattern can be described with the help of Fig. 2.

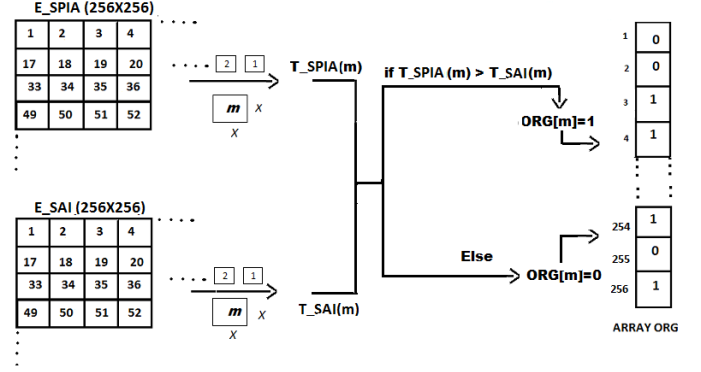


Fig. 2. Algorithmic recursion for obtaining self-learned characteristics (SLC) of low resolution (LR) image where  $T\_SPIA(m)$  and  $T\_SAI(m)$  are Mean Square Error of  $m^{th}$  block in  $E\_SPIA$  and  $E\_SAI$  image respectively.

Suppose the given LR image is of the dimension  $256 \times 256$ . We down sample this image and get low low resolution image (LLR) of the dimension  $128 \times 128$ .

$$LLR(i, j) = LR(2i - 1, 2j - 1) \quad \forall (i, j) \in LR \quad (2)$$

We applied both SPIA and SAI interpolation algorithms on LLR and as a result  $SPIA\_LR$  and  $SAI\_LR$  image of dimension  $256 \times 256$  are obtained. We can get two error images  $E\_SPIA$  and  $E\_SAI$  by subtracting  $SPIA\_LR$  and  $SAI\_LR$  from the LR image. The two error images are shown in Fig. 2 and it illustrates the following:

- 1)  $T\_SPIA(m)$  and  $T\_SAI(m)$  gives Mean Squared Error of  $m^{th}$  block ( $16 \times 16$ ) in  $E\_SPIA$  and  $E\_SAI$  image respectively and  $m$  varies from 1 to 256 (Number of blocks in LR image).
- 2) If  $T\_SPIA(m)$  is less than  $T\_SAI(m)$ , then it signifies that  $m^{th}$  block of LLR image is interpolated by SPIA with better prediction accuracy as compared to block obtained by SAI method. Thus, an array  $ORG$  ( $256 \times 1$ ) is made which stores value 0 in its  $m^{th}$  index.
- 3) If  $T\_SPIA(m)$  in  $E\_SPIA$  is greater than  $T\_SAI(m)$  in  $E\_SAI$ , then  $m^{th}$  index of array  $org$  will store value 1.

So after obtaining self-learned characteristics with the help of LR image and generated two error images, we have made an array  $ORG$  which contains 0's and 1's along with index (indicating position of block). We imprerically found that SAI methods works better on smooth images while SPIA methods works better on detailed images. So a hybrid scheme of combining SAI method and SPIA method based upon the self-learned characteristics is used for best prediction of HR image.

Thus our Proposed algorithm is now further dependent upon the total number of occurrence of 0 ( $ORG\_0$ ) and 1 ( $ORG\_1$ ) in array  $ORG$  which will also state the characteristics (detailed or smooth) of given LR image.

### A. Number of Zeros greater than number of ones in Array ORG

If number of 0's in array ORG is greater than number of 1's, it suggests that a large number of blocks of LLR image are interpolated by SPIA method with better prediction accuracy. It also signifies that these blocks should have higher variation among the pixels. As shown in (2), blocks (8×8) of LLR image are derived from the corresponding blocks (16×16) of LR image. So we can expect that the same characteristics will be followed by the corresponding blocks in LR image.

Our proposed SLCSI algorithm in this case is shown in Fig.3 and it works as follows.

- 1) Before interpolating  $m^{th}$  block of LR image we checked whether  $m^{th}$  position in array ORG is filled by 0 or 1.
- 2) If it is filled by 1 (Org[m]==1) which implies that  $m^{th}$  block of LLR image was interpolated by SAI with better prediction accuracy.
- 3) But we derived that a large number of blocks have higher variations among the pixels. Thus image is detailed.
- 4) So if we interpolate the corresponding  $m^{th}$  block of LR image by SAI method, we may have improvement in prediction accuracy of HR image.

But to make best use of SPIA in such cases, we extended our method of interpolation by using a threshold A (shown in Fig. 4) before interpolating these blocks by SAI method. The threshold A decides the strength of error energy of these blocks. So our further proposed algorithm works as follows :

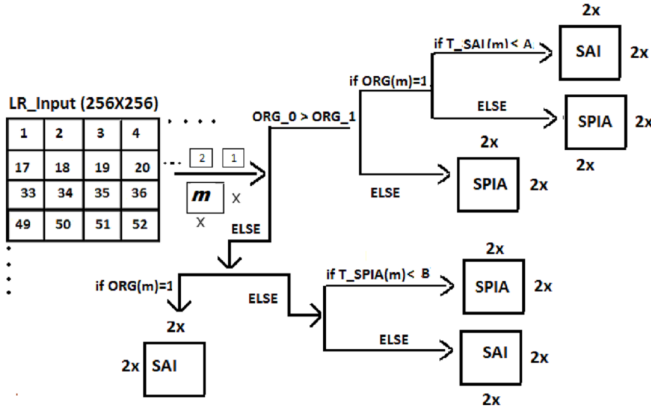


Fig. 3. Image Interpolation based upon the obtained self-learned characteristics.

- 1) If  $T\_SAI(m)$  is less than threshold A, which implies that  $m^{th}$  block of SAI\_LR was predicted with less error energy by SAI method. So, we will interpolate the corresponding  $m^{th}$  blocks of LR image by SAI method.
- 2) Else it implies that  $m^{th}$  block of SAI\_LR was predicted with more error energy by SAI method. Since SAI creates more prediction error which signifies that the block is relatively detailed in nature. So the  $m^{th}$  block in LR image will be interpolated by SPIA so that the prediction error in HR image can be further reduced.

TABLE I  
MSE(SAI), MSE(SPIA), MSE(ERROR\_TH) REFERS TO MEAN SQUARE ERROR OF E\_SAI, E\_SPIA, E\_ORG RESPECTIVELY

Images	Baboon.pgm	Cycle.pgm	Party.pgm
(ORG_0,ORG_1)	(191,65)	(176,80)	(168,88)
MSE (SAI)	612.0	1429.8	2517.1
MSE (SPIA)	547.3	1315.1	2420.8
MSE (Error_Th)	545.6	1305.5	2392.2

Moreover, if the  $m^{th}$  position in array ORG is filled with 0 (Org[m]==0), then we will directly interpolate the  $m^{th}$  block of LR image by SPIA method. As shown in (3) and (4), we calculated a portion of E\_SAI and E\_SPIA whose corresponding blocks in LR image will be interpolated by proposed SLCSI algorithm.

$$E\_ORG(m) = \begin{cases} E\_SAI(m) & \text{if } T\_SAI(m) \leq A \\ E\_SPIA(m) & \text{if } T\_SAI(m) > A \end{cases} \quad (3)$$

```

% Initialize .....
Sum_SPIA = 0, Sum_SAI = 0
% main loop
for m=1 to 256
    if T_SPIA(m) < T_SAI(m)
        Sum_SPIA = Sum_SPIA + T_SPIA(m)
    else
        Sum_SAI = Sum_SAI + T_SAI(m)
    end
end
% threshold A and B .....
A = (Sum_SAI / ORG_1)
B = (Sum_SPIA / ORG_0)
  
```

Fig. 4. Pseudo-C code for calculating thresholds.

$$E\_ORG(m) = E\_SPIA(m) \quad \forall \quad T\_SPIA(m) \quad (4)$$



Fig. 5. Sample images (256×256). (a)Baboon (b) Cycle (c) Party.

To prove efficiency of threshold A in proposed SLCSI algorithm, we had done experiments with some test images (shown in fig.5) and it works as follows

- 1) These images follows the condition such that ORG\_0 is greater than ORG\_1.
- 2) We calculated E\_ORG (256×256) shown in (3) and (4) which is final error image after using threshold.
- 3) We calculated the Mean Square Error of E\_SAI (256×256) and E\_SPIA (256×256) in three different images which is shown in Table 1.

TABLE II  
MSE(SAI), MSE(SPIA), MSE(ERROR\_Th) REFERS TO MEAN SQUARE  
ERROR OF E\_SAI, E\_SPIA, E\_ORG RESPECTIVELY

Images	Peppers.pgm	Boat.pgm	Lena.pgm
(ORG_1,ORG_0)	(191,65)	(141,115)	(192,64)
MSE (SPIA)	139.9	206.5	94.38
MSE (SAI)	97.61	201.2	79.32
MSE (Error_Th)	96.90	199.2	78.86

- 4) We can see that MSE of E\_SPIA ( $256 \times 256$ ) is lower than MSE of E\_SAI. It implies SAI creates more error energy as compared to SPIA.
- 5) So before interpolating these blocks of LR image by SAI, we put a threshold A so that SPIA can be applied to those blocks in LR image whose corresponding blocks in E\_SAI is having more error energy.
- 6) We can conclude from the table 1 that when we used threshold A, MSE of E\_ORG ( $256 \times 256$ ) decreases.

Since LLR is a part of LR image, so we can say that in the interpolation of LR image using threshold will increase the prediction accuracy of HR image.

#### B. Number of Ones greater than number of Zeros in Array ORG

The SLCSI algorithm in this part remains almost same as it was discussed in the previous sub-section and is shown in bottom part of Fig 3. The only difference is that we used threshold B before applying SPIA on the blocks of LR image.



Fig. 6. Sample images ( $256 \times 256$ ). (a) Peppers (b) Boat (c) Lena.

Experiments have been done with test images (shown in fig. 6) to prove the efficiency of threshold B in proposed algorithm. In table 2, we can see that MSE (SAI) is less than MSE (SPIA), so we put a threshold before applying SPIA on the blocks of LR image so that SAI could be applied whose corresponding blocks in E\_SPIA is having more error energy i.e., depending on the values of T\_SPIA(m). Table 2 concludes that by using threshold, the MSE of E\_ORG( $256 \times 256$ ) decreases.

#### IV. SIMULATION RESULTS

For simulation results, we selected images including both smooth and detailed in nature and is shown in Fig. 5, 6 and 7. Objective quality (PSNR) of the proposed algorithm compare to previous methods are shown in Table 3.

Table 3 concludes that SLCSI algorithm consistently ranks the first among all method in terms of PSNR performance. On an average, proposed SLCSI algorithm exceeds NEDI [1],

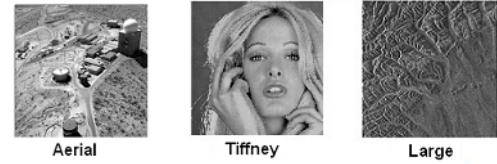


Fig. 7. Sample images ( $256 \times 256$ ). (a) Aerial (b) Tiffney (c) Large.

TABLE III  
RESULTS (PSNR IN DB) OF RECONSTRUCTED HR IMAGE BY DIFFERENT  
METHODS. RESULTS FOR BILINEAR (BILI) AND BICUBIC (BICU)  
METHODS ARE CALCULATED BY STANDARD MATLAB FUNCTION.

Images	BILI	BICU	NEDI	[3]	SPIA	SAI	SLCSI
Baboon	22.03	21.66	22.92	23.04	23.31	23.16	<b>23.38</b>
Cycle	17.29	16.83	18.08	17.94	18.26	17.95	<b>18.38</b>
Party	14.92	14.48	15.66	15.61	15.78	15.57	<b>15.89</b>
Peppers	28.68	28.44	29.14	30.39	30.43	31.87	<b>31.96</b>
Boat	27.12	26.94	28.93	29.30	29.38	29.74	<b>29.82</b>
Lena	30.20	30.12	33.10	33.80	33.70	34.74	<b>34.79</b>
Aerial	20.75	20.36	21.70	21.78	21.84	21.79	<b>21.92</b>
Large	18.45	17.99	19.27	19.16	19.40	19.13	<b>19.48</b>
Tiffney	27.65	27.30	28.99	29.35	29.84	30.02	<b>30.10</b>
Average	23.01	22.68	24.20	24.49	24.66	24.89	<b>25.08</b>

SPIA [6] and SAI [4] in PSNR by 0.88, 0.42 and 0.19 db respectively.

#### V. CONCLUSIONS

In this paper, we proposed a new image interpolation algorithm which incorporate the switching of SAI method and SPIA method on block by block basis. Switching of interpolation algorithm is based upon the self learned characteristics of the available LR image and threshold (calculated using SLC). Since low LR image (LLR) follows the characteristics of LR image, so we differentiated the error pattern in interpolation of LR image to HR image. We conclude that performance of SAI and SPIA is highly dependent upon the characteristics of the input LR image whereas the proposed interpolation algorithm invariably works best irrespective of the input image.

#### REFERENCES

- [1] Xin Li and Michael T. Orchard "New Edge-Directed Interpolation," in *IEEE Transaction On Image Processing*, Vol. 10, No. 10, October 2001.
- [2] Vinit Jakhethiya and Anil K. Tiwari, "A Survey on image interpolation methods," in *International Conference on Digital Image Processing*, 2010.
- [3] Lei Zhang and Xiaolin Wu "An Edge-Guided Image Interpolation Algorithm via Directional Filtering and Data Fusion," in *IEEE Transaction On Image Processing*, Vol. 15, No. 8, August 2006.
- [4] Xiangjun Zhang and Xiaolin Wu "Image Interpolation by Adaptive 2-D Autoregressive Modeling and Soft-Decision Estimation," in *IEEE Transaction On Image Processing*, Vol. 17, No. 6, June 2008.
- [5] Tinku Acharya and Ping-Sing Tsai, "Computational Foundations of Image Interpolation Algorithms," in *ACM Ubiquity Vol. 8*, 2007.
- [6] Vinit Jakhethiya and Anil K. Tiwari, "Image interpolation by adaptive 2-D autoregressive modeling," in *International Conference on Digital Image Processing*, 2010.