ACCURACY IMPROVEMENTS AND ARTIFACTS REMOVAL IN EDGE BASED IMAGE INTERPOLATION

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Abstract: In this paper we analyse the problem of general purpose image upscaling that preserves edge features and natural appearance and we present the results of subjective and objective evaluation of images interpolated using different algorithms. In particular, we consider the well-known NEDI (New Edge Directed Interpolation, Li and Orchard, 2001) method, showing that by modifying it in order to reduce numerical instability and making the region used to estimate the low resolution covariance adaptive, it is possible to obtain relevant improvements in the interpolation quality. The implementation of the new algorithm (iNEDI, improved New Edge Directed Interpolation), even if computationally heavy (as the Li and Orchard's method), obtained, in both subjective and objective tests, quality scores that are notably higher than those obtained with NEDI and other methods presented in the literature.

1 INTRODUCTION

Image upscaling through pixel interpolation is used in different fields to create high resolution images with a ”natural” appearance from low resolution acquired data. Applications of this procedure can be found in image viewing/processing software, photographic printing and Computer Graphics. Real time algorithms can also be applied to increase the perceived quality of video streaming or textures in virtual navigation tools.
In general, the procedure tries to recover missing information by assuming that there is a known relationship between a low resolution image and the same image acquired with an high resolution sensor. General purpose algorithms for the upsampling of single images, unlike methods that use multiple images to generate high resolution ones (usually referred as super-resolution algorithms) do not add real information on the scene and are not useful as pre-processing steps in vision based applications. They are, however, interesting for researcher due to the necessity of removing pixelization, blurring and other annoying artifacts affecting images enlarged with trivial techniques (i.e pixel replication or bilinear interpolation). Several algorithms have been therefore proposed in literature to obtain better results and several patents have been obtained for ”smart” interpolation techniques.
Few systematic comparisons have been, however, presented and it is difficult to determine which method is the best suited for a selected application. In this paper we present (section 2) a short review on the methods proposed for image upsampling. We then focus our attention on the NEDI method (Li and Orchard, 2001) that seem to provide very good results, even if at the cost of a large computational complexity that limits its fields of application. We analyse (section 3) the drawbacks of the method and propose a modified algorithm (iNEDI, improved New Edge Directed Interpolation) that reduces the effects of most of them. In section 5 we show that the new method provides the best results in a large set of objective and subjective tests performed to compare the quality of differently upsampled natural images.

2 INTERPOLATION APPROACHES: A REVIEW

The simplest image interpolation algorithms are based on linear filtering. Values of the new pixels are obtained by assuming that the values of the image

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function in the new pixel locations can be computed as a linear combination of the values of the original pixels close to the new position. Nearest neighbor, bilinear and bicubic interpolations, kernel based (i.e. Lanczos) methods are widely applied for the task and implemented in image viewers and image processing tools. These methods are computationally efficient and especially the bicubic interpolation (fitting a cubic function on the 16 closest neighbors) provides visually good images, that do not appear, however, ”natural” due to blur and jagged contours.

Several methods have been used to improve the results, in order to print or display on screens upscaled images that are perceived of better quality, even if obtained from the same low resolution original data.

Non linear methods are usually based on an implicit or explicit search of local image features and on a subsequent local adaptation of the interpolation function to the (low resolution) extracted features. In (Lu et al., 2003) the interpolation is guided by the output of directional filter banks. In (Schultz and Stevenson, 1994) the high resolution image is modeled as a Gibbs-Markov Field and the zooming procedure is obtained optimizing convex functionals. In (Takahashi and Taguchi, 2002) a Laplacian Pyramid decomposition is performed and used for the prediction of local high frequency components. In (Morse and Schwartzwald, 2001) an iterative method based on level set theory and isophotes (i.e. curves of constant intensity) smoothing is applied with some ad hoc rules to prevent change in topology and other side effects. The approach of (Muresan and Parks, 2004) consists of first determining the local quadratic signal from local patches, then estimating missing samples applying optimal recovery.

Efficient approaches that can be applied in time critical tasks consist of using simple heuristics to determine the edge direction and interpolate directionally along the edge direction. Example of this case are the Data Dependent Triangulation (Su and Willis, 2004) and the methods proposed in (Battiato et al., 2002) and (Chen et al., 2005). In (Wang and Ward, 2007) an interpolation kernel that adapts to the local orientation of isophotes is used to reduce artifacts in bilinear interpolation. Also in (Cha and Kim, 2007) authors use bininear interpolation and then try to amend the error by utilizing the interpolation error theorem in an edge-adaptive way.

Other methods try to improve the accuracy of the interpolation characterizing the edge features in a larger region around the point: this is the case of the NEDI technique (Li and Orchard, 2001) that seem to provide the best results for natural images, even in the case of large scale factors. This is the reason we start our analysis describing this technique and then propose several improvements.

Of course better resolution-enhanced images could be obtained if some *a priori* knowledge on the relationship between low resolution and high resolution images is available for the scene being considered. For this reason some authors have tried to exploit pixel or texture statistics or databases of example images to obtain good high resolution ”hallucinated” images (Atkins et al., 2001; Freeman et al., 2002; Sun et al., 2003). The huge variety of natural textures and scales makes, however, quite difficult a general purpose use of similar techniques, though they can be efficiently applied to particular tasks (i.e. search of patterns like faces, trees, etc.).

3 NEW EDGE DIRECTED INTERPOLATION

The NEDI algorithm (Li and Orchard, 2001) is based on the assumption that the low resolution covariance of pixel values in 5 pixel cross-like configurations, is a good approximation of the high resolution covariance. The image is therefore approximately doubled in size by first putting original NxN pixels I_{LR} in an enlarged $(2N-1)x(2N-1)$ grid I (see Fig. 1) and then filling in two steps the missing values as weighted averages of the four closest valued pixels. Fig. 1 show the first step, inserting the new values in positions $2i+1, 2j+1$, with the formula:

$$I_{2i+1,2j+1} = \vec{\alpha} \cdot (I_{2i,2j}, I_{2i,2j+2}, I_{2i+2,2j}, I_{2i+2,2j+2}). \quad (1)$$

The second step fills the remaining gaps in the same way after a 45 degrees rotation of the grid (Fig. 2).

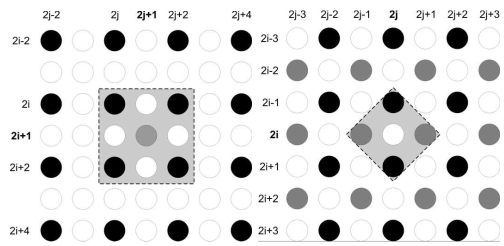

Figure 1: The two step NEDI interpolation. Original NxN pixel are placed in a 2N-1x2N-1 grid. Pixels at odd positions (2i+1,2j+1) are then filled with the NEDI method (left) as weighted sums of the 4 diagonal neighbors. The remaining empty pixels are then filled in the same way after a 45^O rotation of the grid.

The coefficient of the linear interpolation are the elements of the vector $\vec{\alpha} = (\alpha_0, \alpha_1, \alpha_2, \alpha_3)$ (Fig. 2).

NEDI estimate these α_i by solving an unconstrained system of linear equations. The system is obtained by assuming that the coefficients linking each pixel with its four diagonal neighbors do not change with scale (i.e. the relationship is maintained on subsampled/upscaled images) and that they are constant in a squared window W centered in the interested pixel location. Fig. 2 shows an example: assuming that each valued pixel (painted in gray) of the 4*x*4 (7x7 in the upscaled image) pixel window W centered in $\vec{x} = (2i+1, 2j+1)$ can be obtained as a weighted sum of the diagonal neighbors with equal weights, we can write a system of equations:

$$\mathbf{C}\vec{\alpha} = \vec{y} \tag{2}$$

where
$\mathbf{C} =$

$$\begin{pmatrix} I_{h_1-1,k_1-1} & I_{h_1-1,k_1+1} & I_{h_1+1,k_1-1} & I_{h_1+1,k_1+1} \\ I_{h_2-1,k_2-1} & I_{h_2-1,k_2+1} & I_{h_2+1,k_2-1} & I_{h_2+1,K_2+1} \\ \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots \\ I_{h_N-1,k_N-1} & I_{h_N-1,k_N+1} & I_{h_N+1,k_N-1} & I_{h_N+1,k_N+1} \end{pmatrix}$$

$h, k \in W(2i+1, 2j+1)$

and $\quad \vec{y} = (I_{h_1,k_1}, I_{h_2,k_2}, I_{h_3,k_3}, \ldots, I_{h_N,k_N})^T$.

$W(2i+1, 2j+1)$ is the set of valued pixels in the squared window centered in $(2i+1, 2j+1)$ (i.e. the light gray area of Fig. 2). (h_n, k_n) are the coordinates of the n^{th} pixel inside the window. The system is solved by a least squares method to obtain the α_i coefficients.

4 LIMITS OF NEDI ALGORITHM AND SOLUTIONS PROPOSED (INEDI)

The NEDI technique provides good results due to the fact that it adapts locally at each resolution the interpolating surface assuming local regularity in curvature. The assumption of local stationarity of the covariance is violated in several cases and the analysis of these cases can be exploited to improve the interpolation results. The use of large and squared windows to generate the over-constrained system (2) causes errors and artifacts due to high frequency components and that can be only partially removed by setting thresholds on the residual of the coefficient computation or by using robust estimators. Indeed, the use of generic robust estimators does not remove artifacts, because they may introduce non local effects and ad hoc strategies should be applied.

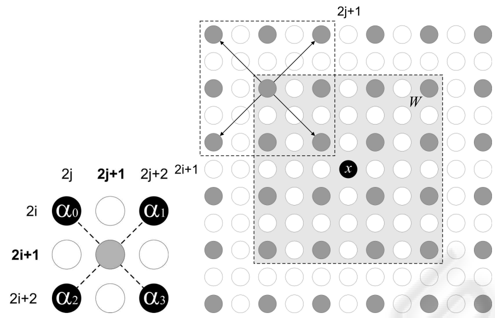

Figure 2: In the NEDI method, the four coefficient used to compute the interpolated value (left) are computed assuming that in a squared window around the point each pixel of the low resolution image is related through the same coefficients to its 4 closest neighbors.

We identified several problems in the original formulation and proposed some modifications to increase the interpolation accuracy. The final result is a modified technique, referred in the following as iNEDI, improved New Edge Directed Interpolation, implementing all the improvements proposed and that are summarized in the following subsections.

4.1 Windows Shape

A first minor problem that, however, can be removed is that the use of squared windows is not optimal because it can introduce directional artifacts and anyway makes the algorithm non isotropic. These effects can be reduced by simply computing the parameters on approximately circular windows (except, in our case, for the pixels excluded by the edge segmentation described in the following).

4.2 Non Edge Pixels Handling

It is evident that when the four pixels used to calculate the interpolated ones have a similar gray level, there is no need to compute the NEDI coefficients, if the covariance is stationary, a small error causes a bad conditioning of the solution, even if, on the other hand the use of linear interpolation changes slightly the results. This problem is already handled in the original NEDI formulation, moving to bilinear interpolation if local gray level variation is above a fixed threshold THR. We adopted a similar solution, but we applied the bicubic approximation in low frequency regions. This choice, of course, do not give improvements in image quality when THR is low. It gives, however, the possibility of obtaining a good tradeoff between edge direction preservation, accuracy and speed using higher values of the threshold (i.e. using iNEDI only for strong edges).

4.3 Edge ”Segmentation”

The main problem in the NEDI formulation is how to ensure that the window used for the estimation belongs almost completely to the same ”edge”. For each point $\vec{x}$ in the enlarged grid to be fitted, the ideal window where points should be inserted in C and $\vec{y}$ should be a connected region including the 4 valued pixel pixel closest to $\vec{x}$ where local curvatures are smoothly changing. This is a condition that is stronger than the constant covariance constraint, that does not guarantee the absence of high component frequencies in the local fit.

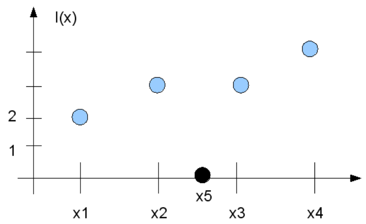

Figure 3: A simple 1D interpolation example showing that an exact constant covariance interpolation may create completely wrong results. Assuming that each pixel at the low resolution can be obtained as a weighted sum of the two neighbors and assuming weights locally constant, we obtain the black pixel as the one interpolating the profile in x_5.

This fact can be shown with a 1D example. Consider the plot of Fig. 3, and suppose we want to increase the resolution by estimating an interpolated value in x_5 assuming that $I(x_5) = \alpha_1 I(x_2) + \alpha_2 I(x_3)$ and that α_1,α_2 can be estimated from the neighboring pixels at the coarse scale $I(x_1), I(x_2), I(x_3), I(x_4)$. Assuming $I(x_2) = \alpha_1 I(x_1) + \alpha_2 I(x_3)$ and $I(x_3) = \alpha_1 I(x_2) + \alpha_2 I(x_4)$, the exact solution is:

$$\alpha_1 = \frac{I(x_2)I(x_4) - I(x_3)^2}{I(x_1)I(x_4) - I(x_3)I(x_2)}$$
$$\alpha_2 = \frac{I(x_1)I(x_3) - I(x_2)^2}{I(x_1)I(x_4) - I(x_3)I(x_2)} \tag{3}$$

leading to an interpolated value of:

$$I(x_5) = \frac{I(x_2)^2 I(x_4) - I(x_3)^2 I(x_2) - I(x_2)^2 I(x_3) + I(x_3)^2 I(x_1)}{I(x_1)I(x_4) - I(x_3)I(x_2)} \tag{4}$$

With the example values of Fig. 3, with a large variation in local curvature, we have an ”exact” constant covariance based interpolation between with an absurd high frequency. This problem is usually less relevant if we have a least squares formulation with several independent conditions and the profile is locally smooth. It is clear, however, that the low value of the residual of the best fit cannot be used as the unique condition to determine if the α coefficients computed with NEDI are reasonable. This is why we decided to perform an *a priori* segmentation of the edge region around the interested point and to control and possibly reject a posteriori the interpolated values in case of too high frequencies.

To segment the connected ”edge region”, we used a sort of region growing method defined as follows: -Start from 4 valued neighboring pixels of the central point and add iteratively neighbors (in the original grid) of these pixels with the following properties:

- The gray level between the maximum and the minimum value of the 4 neighbors is not lesser than THR (as in the central point).
- The gray level of each pixel is not larger than the maximum value of the gray level of the 4 neighbors of the central incremented by a threshold $MARGIN$ and not lower than the minimum of the 4 neighbors of the central point decremented by the same $MARGIN$.
- The Euclidean distance between the pixel and the central point is less than r.

-Enlarge the ”edge” region with the same rules by increasing r up to a maximum value R if the increment of the radius correspond to a decrement if the normalized residual of the least squares fit.

With this selective procedure and the control on the residual, we increase the probability of obtaining a good interpolation, but there is still the possibility of having unwanted high frequencies (that are not excluded by the constant covariance condition and may occur in case of a small number of samples in the fit). For this reason we put a further constraint by replacing any interpolated value outside the intensity range of the four neighbors with the closest of the values delimiting that range (i.e. maximum or minimum).

4.4 Matrix Conditioning and Error Propagation

Also when clearly bad regions are eliminated with the ”edge segmentation” procedure, the overconstrained system (2) is often poorly conditioned and a small error in $\vec{y}$ can cause a large error in the estimated $\hat{\alpha}$. The sensitivity of the solution to the bad conditioning depends on the relative error on data. A simple trick to improve the solution accuracy is to add a constant value to the gray levels, in order to have all values far from zero. This simple change is effective in reducing artifacts and wrong estimates.

Another issue that should be considered is that for a typical edge we have that the signal is changing along a fixed direction with constant curvature. In this case the overconstrained system is clearly badly conditioned due to the rank deficiency of the problem (the expected rank of the matrix is 2 and not 4.). This means that the problem of bad conditioning is almost always verified and that rejecting neighborhood with bad condition numbers would result in dropping the NEDI method almost everywhere.

The fact that **C** is rank deficient, means that the solution to the least squares problem is not unique, i.e. there are many vectors $\vec{\alpha}^*$ that minimize $||\mathbf{C}\vec{\alpha}-\vec{y}||_2$. We can therefore look for a reliable choice among the infinite number of possible solutions.

A method that is often used to find an unique solution is to select the minimum norm solution, that is obtained through the computation of the Moore-Penrose pseudo inverse. If we assume that the local four pixel configuration is the sum of a term exactly modeled by the constant covariance model plus an error term (i.e., for an odd point in the first step: $\vec{I_4} = (I_{2i,2j}, I_{2i,2j+2}, I_{2i+2,2j}, I_{2i+2,2j+2}) = \vec{I_0} + \vec{I_{err}}$), the squared error on the interpolated value $I_{2i+1,2j+1} = \vec{\alpha}^* \cdot \vec{I_4}$ is $(\vec{\alpha}^* \cdot \vec{I_{err}})^2$ and it is in general lowered by choosing the minimum norm solution for α^*. We solved therefore the overconstrained system using this method.

4.5 Global Brightness Invariance

With the NEDI method, interpolated pixel values change with the global brightness, i.e. they do not depend only on differences between neighboring values, but also on the absolute value. This effect can be easily removed by changing the NEDI constraint by subtracting the average of the four neighbors intensities from the values inserted in C and $\vec{y}$, i.e. replacing C with

$$\mathbf{C}' =$$

$$\begin{pmatrix} I_{h_1-1,k_1-1}-\overline{I}_{h_1,k_1} & I_{h_1-1,k_1+1}-\overline{I}_{h_1,k_1} & \dots & \dots \\ I_{h_2-1,k_2-1}-\overline{I}_{h_2,k_2} & I_{h_2-1,k_2+1}-\overline{I}_{h_2,k_2} & \dots & \dots \\ \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots \\ I_{h_N-1,k_N-1}-\overline{I}_{h_N,k_N} & I_{h_N-1,k_N+1}-\overline{I}_{h_N,k_N} & \dots & \dots \end{pmatrix}$$

$h,k \in W(i,j)$

and $\vec{y}$ with

$$\vec{y'} = (I_{h_1,k_1}-\overline{I}_{h_1,k_1}, I_{h_2,k_2}-\overline{I}_{h_2,k_2}, \dots, I_{h_N,k_N}-\overline{I}_{h_N,k_N})^T$$

where $\overline{I}_{h,k} = \frac{(I_{h_1-1,k_1-1}+I_{h_1-1,k_1+1}+I_{h_1+1,k_1-1}+I_{h_1+1,k_1+1})}{4}$.

$I(i,j)$ is then clearly obtained as:

$$I(i,j) = \alpha' \cdot (I_{i-1,j-1}, I_{i-1,j+1}, I_{i+1,j-1}, I_{i+1,j+1}) + \overline{I}_{i,j}.$$

This change clearly makes the matrix $\mathbf{C}'$ rank deficient, but, as discussed before, the solution is still possible with the pseudo-inverse. Experimental results show, however, that the advantages obtained in the interpolation of natural images in this way is small.

5 EXPERIMENTAL RESULTS

The modified technique described has been widely tested and compared with other methods found in literature as well as with the original NEDI. The new method has been has been implemented in Matlab and the code is publicly available at the web site *http://inedi.tecnick.com*. We have also coded and tested other methods (Chen's and Isophote based) while for the linear methods we used the basic image processing Matlab functions. The NEDI implementation used is the original Matlab code kindly provided to us by prof. Xin Li.

5.1 Enlarged Subsampled Images

A simple test often used in literature to measure quantitatively the interpolation accuracy consists of generating low resolution images by filtering and subsampling high resolution ones and then measure the difference between the differently re-upsized images and the original one. The measure used to compute this difference is mainly the Peak Signal to Noise Ratio, defined as:

$$PSNR = 20\log_{10}\frac{MAXPIX}{\frac{\sum_{i=1}^{W}\sum_{j=1}^{H}(I_{exp}(i,j)-I_{orig}(i,j))^2}{(W*H)}} \tag{5}$$

where $I_{exp}(i,j)$ is the zoomed subsampled image, I_{orig} the original one, W and H the image dimensions and $MAXPIX$ the end scale value of the pixel intensity. The value measures therefore how much the interpolation method is able to guess the correct image values at unknown locations for each particular scene/image considered.

Due to the fact that the method is strongly dependent on the scene and on the imaging procedure, it is necessary to test the results on a relevant set of images and/or on complex images representing different natural textures. We performed our tests on an original set of 9 1025x1025 images, transformed in low resolution ones (256x256 and 128x128) and then upscaled (2x,4x) with different algorithms. Images (see Fig. 4) are all natural and present a great variety of textures and local frequencies. Note that the (511x511 or 512x512) reference images used to compute the PSNR are different for different interpolation algorithms due to the different image shifts introduced by the various technique. An half pixel image shift not compensated may compromise the correctness of the comparison and lead to a wrong estimate of algorithms performances. Tables 1 and 2 show the PSNR values for each image obtained with NEDI and iNEDI algorithms and other selected techniques (bilinear and bicubic, an iterative method based on isophote smoothing based on (Morse and Schwartzwald, 2001) and the fast edge based method describedin (Chen et al., 2005) for 2x and 4x enlargement. It is evident that the improvements proposed give a relevant increase in the measured quality of NEDI and that the accuracy of the reconstruction is higher than those obtained with the other techniques.

Figure 4: Images used for the quantitative comparison.

One fact that may appear surprising is that the performances of the original NEDI and of the other two literature algorithm presented are worse than the results of the bicubic interpolation. Our comparison was performed carefully, using the bicubic approximation implemented in MATLAB, the original Xin Li implementation for original NEDI and following the algorithms description of other authors. The parameters used were chosen with a trial and error method in order to minimize the reconstruction error.
It should be considered, however, that the good results of the bicubic interpolation does not mean that it is surely better than other methods: original NEDI, as well as the other edge based method tested (Chen, Isophote), are effective in removing the typical artifacts of the bicubic and bilinear interpolation (i.e. jagged contours). The lower PSNR is probably due to the other kinds of artifacts affecting NEDI and excessive smoothing of the other approaches.

Figure 5: 8X enlarged images. Jagged contours are evident in nearest neighbor and bicubic interpolation (left, center). The NEDI interpolation (right), present sharp edges, even if introduces different artifacts and perform often worser than the bicubic method in quantitative comparisons. Our improvements to the method reduce evidently these effects.

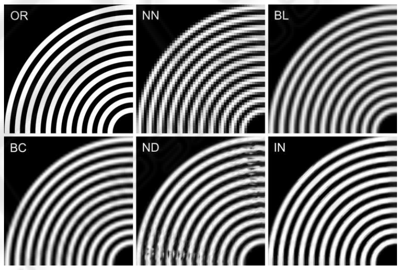

Figure 6: Original artificial image (OR) and 8X reduced/enlarged images (NN=Nearest Neighbor, BL=Bilinear interpolation, BC=Bicubic interpolation, ND=Nedi, IN=iNedi). The NEDI interpolation removes jagged contours, but introduces directional artifacts. iNedi modifications remove these effects.

We also performed a test on an artificial image to show the improvements of iNEDI over NEDI in the removal of directional artifacts. Fig.6 shows an original b&w image with concentric circles and the subsampled and 8x enlarged versions obtained with pixel replication, bilinear, bicubic, NEDI and iNEDI interpolations. INEDI clearly removes not only the jagged lines effects of the linear methods, but also removes the directional artifacts of NEDI. The PSNR value is increased by more than 3 dB.

To compare the iNEDI technique with other techniques available on commercial software, we also tested the implemented method on a test image provided on the internet site http://www.generalcathexis.com/interpolation.html where several interpolation methods implemented on the SAR Image Processor package are compared. The iNEDI algorithm provided a PSNR relevantly higher (1dB) than the best one in the reported comparison (see Table 3).

Table 1: PSNR values (dB) obtained on 2x enlarged images with different methods. The modified edge directed interpolation obtained an average increment of 0.85 dB on the original Xin Li technique and is clearly superior to all the other methods.

Im	iNEDI	NEDI	Bicub.	Bilin.	Chen	Isoph.
1	30.22	29.58	30.42	28.88	29.19	29.05
2	38.10	37.33	37.81	35.27	36.33	36.27
3	29.45	28.64	29.91	28.23	28.41	27.91
4	29.10	27.47	28.27	25.80	26.82	27.02
5	32.95	31.98	33.48	31.36	31.72	32.10
6	33.68	32.57	32.15	30.30	31.50	32.26
7	37.46	36.92	36.33	34.38	35.75	36.54
8	36.78	36.21	36.20	33.68	34.95	35.49
9	34.77	34.11	34.40	32.56	33.55	33.76
Av	33.61	32.76	33.22	31.16	32.02	32.27

Table 2: PSNR values (dB) obtained on 4x enlarged images with different methods. The modified edge directed interpolation obtained an average increment of 0.85 dB on the original Xin Li technique and is clearly superior to all the other methods.

Im	iNEDI	NEDI	Bicub	Bilin	Chen	Isoph
1	24.77	24.21	24.76	24.10	23.98	23.82
2	30.10	29.42	29.70	28.37	28.53	28.52
3	23.80	23.22	23.89	23.16	22.88	22.50
4	21.30	19.95	20.71	19.62	19.64	19.63
5	25.90	25.38	26.11	25.22	25.11	24.96
6	27.10	25.69	25.79	24.72	25.04	25.34
7	30.70	30.04	29.68	28.44	29.12	29.90
8	29.24	28.31	28.27	26.85	27.32	27.89
9	28.68	27.73	28.02	26.91	27.18	27.34
Av	26.84	25.99	26.33	25.27	25.42	25.54

5.2 Qualitative Scores

A group of 24 people have been asked to give a "qualitative" judgment on 12 color images originally of 80x60 pixels and enlarged (independently for each color channel) of a factor 8 with iNEDI and NEDI algorithms as well as with bicubic and bilinear interpolation.

Figure 7: Color images used for the qualitative comparison (Results in Table 4).

Table 3: PSNR obtained with the proposed iNEDI algorithm on a test image compared with the results of several methods reported on the site http://www.general-cathexis.com/interpolation.html.

Method	PSNR [dB]
iNEDI	29.65
DDL with SuperRez Postproc.	28.65
LAD Deconvolution	28.57
Pseudonverse with SR Postproc.	28.57
Jensen Zhao Xin Li	27.90
Zhao Xin Li	27.65
Bicubic	27.49
Triangulation	27.10
Bilinear	26.92
Nearest neighbor	26.19

The qualitative judgment has been performed sorting the images from the worst (1) to the best (4). The qualitative test is really important in choosing an optimal algorithm because the main application of this kind of algorithm consists in the improvement of the perceived image quality in printing or image display applications. The results obtained (Table 4) confirmed the results of the analysis based on the PSNR. In fact, the original NEDI score is lower than that obtained with the bicubic approximation. This is due to the relevant artifacts of the technique, that preserves well discontinuities and creates sharp edges, but also creates evident "oil painting" artifacts that makes the image unnatural. This problem is revealed by an higher reconstruction error, but appear also clear to the human eye. The edge segmentation of the iNEDI method reduces relevantly these artifacts, creating natural images still more similar to real high resolution photos than those obtained with bicubic interpolation.

Figure 8: Artifacts reduction obtained with the iNEDI method(right) with respect to NEDI (left): non local effects are clearly reduced by adapting window shapes and size, discarding high frequency interpolated values and optimizing the least squares procedure.

Table 4: Average position (1-4) in a qualitative comparison performed by 24 subjects on 12 images enlarged (8x) with different methods.

Im.	iNEDI	NEDI	Bicubic	Bilinear
1	3.75	2.92	2.13	1.21
2	4.00	2.83	2.00	1.17
3	3.96	2.25	2.54	1.25
4	3.75	2.29	2.67	1.29
5	3.58	2.42	2.67	1.33
6	3.96	2.04	2.63	1.38
7	3.79	2.00	2.88	1.33
8	3.83	1.88	2.96	1.33
9	3.75	2.29	2.75	1.21
10	3.79	1.71	3.08	1.42
11	3.88	2.08	2.75	1.29
12	3.75	2.29	2.67	1.29
Avg.	3.82	2.25	2.64	1.29

6 DISCUSSION

We presented an analysis of popular methods to enlarge natural images without any additional information and several subjective and objective experimental tests comparing the performances of different algorithms. In particular, we introduced and motivated several improvements to the well known Li and Orchard's NEDI method, obtaining a new algorithm, iNEDI, that provides the best results among all the tested methods, even if at the cost of a huge computational complexity. Images enlarged with the proposed technique appear, in fact, more natural and less smoothed than those obtained with other approaches presented in literature and both psychological and quantitative tests measuring differences between enlarged subsampled photos and original ones confirm this fact. For selected applications (i.e. printing or off line extrapolation of high resolution textures from low resolution data) the relevant computational effort is not a problem, while for applications requiring a fast image processing (i.e. improving quality of video streaming), different methods should be applied, even if the algorithm can be optimized and parallelized. We are currently investigating new edge based methods that seem to provide similar results with relevantly low computational complexity.

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