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Enlargement of Image Based Upon Interpolation Techniques

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Abstract- For real time applications, simple linear or cubic interpolation and FCBI (Fast Curvature Based Interpolation) algorithms are applied for the task of enlargement of images without changing super resolution (low resolution and high resolution), but the results obtained are not really satisfactory, being affected by relevant artifacts like blurring and jaggies. In this paper we describe a new method (ICBI, Iterative Curvature Based Interpolation) based on a two-step grid filling and an iterative correction of the interpolated pixels obtained by minimizing an objective function depending on the second order directional derivatives of the image intensity. We need to compare ICBI with FCBI in two cases that is PSNR (Peak Signal to Noise Ratio) test and time calculations for ICBI and FCBI.

We show that the constraints used to derive the function are related with those applied in another well-known interpolation method providing good results. The high quality of the images enlarged with the new method is demonstrated with objective and subjective tests, and PSNR for ICBI is 30.085 dB (ZF=002), 23.833dB (ZF=004).

Keywords- Fast Curvature Based Interpolation, Iterative Curvature Based Interpolation, Fast Methods And The NEDI Algorithm, Perceptually-Inspired An Edge-Directed Color, Image Super- Resolution, New Edge –Directed Interpolation

I. INTRODUCTION

Image up scaling, or single image super-resolution has recently become a hot topic in computer vision and computer graphics communities due to the increasing number of practical applications of the algorithms proposed. Image up scaling (and more generally image interpolation) methods are implemented in a variety of computer tools like printers, digital TV, media players, image processing packages, graphics renderers and so on. The problem is quite simple to be described, we need to obtain a digital image to be represented on a large bitmap from original data sampled in a smaller grid, and this image should look like it had been acquired with a sensor having the resolution of the up scaled image or, at least, present a "natural" texture.

Methods that are commonly applied to solve the problem (i.e. pixel replication, bilinear or bicubic interpolation) does not fulfil these requirements, creating images that are affected by visual artifacts like pixelization, jagged contours, over- smoothing. For this reason a lot of improved algorithms have been presented in literature. They obviously rely on the assumption that, in natural images, high frequency components are not equally probable if low frequency components are known and a good algorithm is able to guess the image pattern that would have been created by a higher resolution sensor better than other methods.

The relationship between high resolution and low resolution patterns can be learned from examples and, for this reason, several researchers proposed to recover a statistical model of it from a training set. Approaches like those presented try to classify patches according to the local edge appearance, applying different interpolation strategies depending on the results. More sophisticated techniques learn the correspondence between high resolution and low resolution image patches solving the problem of locally merging different results to generate a continuous output. Algorithms of this kind can provide very good even if they need a sufficiently representative set of examples. A possible way to avoid the use of training images has been proposed where patch recurrence in single images at different scales and with different sub pixel alignment is used in a framework similar to classic multi-frame super-resolution.

II. EXISTING SYSTEMS

Interpolation is the process of determining the values of a function at positions lying between its samples. It achieves this process by fitting a continuous function through the discrete input samples. This permits input values to be evaluated at arbitrary positions in the input, not just those defined at the sample points. While sampling generates an infinite bandwidth signal from one that is band limited, interpolation plays an opposite role: it reduces the bandwidth of a signal by applying a low-pass filter to the discrete signal. That is, interpolation reconstructs the signal lost in the sampling process by smoothing the data samples with an interpolation function.

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The process of interpolation is one of the fundamental operations in image processing. The image quality highly depends on the used interpolation technique. The interpolation techniques are divided into two categories, deterministic and statistical interpolation techniques. The difference is that deterministic interpolation techniques assume a certain variability between the sample points, such as linearity in case of linear interpolation. Statistical interpolation methods approximate the signal by minimizing the estimation error. This approximation process may result in original sample values not being replicated. In this interpolation, we are mainly concerned about image interpolation. However, interpolation in two dimensions for the general case is sometimes difficult to describe. For gridded data, the n-dimensional interpolation function can be described as the product of n one-dimensional interpolation functions. Therefore it is permitted to look at one dimensional interpolation functions to discuss the behavior of the n-dimensional interpolation functions.

A. Interpolation Kernels

The numerical accuracy and computational cost of interpolation algorithms are directly tied to the interpolation kernel. As a result, interpolation kernels are the target of design and analysis. Here, analysis is applied to the 1-D case. Interpolation in 2-D is a simple extension of the 1-D case. In addition, data samples are assumed to be equally spaced along each dimension. This restriction causes no serious problem because images are usually defined on regular grids.

B. Nearest Neighbor

The simplest interpolation from a computational standpoint is the nearest neighbor, where each interpolated output pixel is assigned the value of the nearest sample point in the input image. This technique is also known as point shioft algorithm and pixel replication. The interpolation kernel for the nearest neighbor algorithm is defined as

$$h(x) = \begin{cases} 1 \rightarrow 0 \le |x| < 0.5 \\ 0 \rightarrow 0.5 \le |x| \end{cases} \quad (1)$$

The frequency response of the nearest neighbor kernel is

$$H(\omega) = \text{sinc}(\frac{\omega}{2}) \quad (2)$$

Convolution in the spatial domain with the rectangle function h is equivalent in the frequency domain to multiplication with a sinc function.

C. Linear Interpolation

Linear interpolation is a first degree method that passes a straight line through every two consecutive points of the input signal. In the spatial domain, linear interpolation is equivalent to convolving the sampled input with the following kernel.

$$h(x) = \begin{cases} 1 - |x| \rightarrow 0 \le |x| < 1 \\ 0 \rightarrow 1 \le |x| \end{cases} \quad (3)$$

The frequency response of the linear interpolation kernel is

$$H(\omega) = \text{sinc}^2(\frac{\omega}{2}) \quad (4)$$

This kernel is also called triangle filter, roof function or Bartlett window. The frequency response of the linear interpolation kernel is superior to that of the nearest neighbor interpolation function.

D. Bicubic Interpolation

Bicubic is a third degree interpolation algorithm that fairly well approximates the theoretically optimum sinc interpolation function. The kernel is composed of piecewise cubic polynomials defined on subintervals (-2, -1), (-1, 0), (0, 1) and (1, 2). Outside this interval the interpolation kernel is zero. The kernel is of form:

$$h(x) = \begin{cases} (a+2)|x|^3 - (a+3)|x|^2 + 1 \rightarrow 0 \le |x| < 1 \\ a|x|^3 - 5a|x|^2 + 8a|x| - 4a \rightarrow 1 \le |x < 2| \\ 0 \rightarrow 2 \le |x| \end{cases} \quad (5)$$

The frequency response is

$$R(\omega) = \frac{12}{\omega^2}(\text{sinc}^2(\frac{\omega}{2}) - \text{sinc}(\omega)) + a\frac{8}{\omega^2}(3\text{sinc}^2(\omega) - 2\text{sinc}(\omega) - \text{sinc}(2\omega)) \quad (6)$$

E. Disadvantages of Existing System

Affected by relevant artifacts like Blurring, Jaggies, Pixelization, Over Smoothing, High computational complexity

III. PROBLEM DEFINITION

Normally digital images need to be integrated into various types of media. Distribution of high resolution images in limited bandwidth is impractical. As the available low resolution images need to be displayed or printed in high resolution devices, image magnification or zooming is done. The main issues taken into consideration while zooming are pixelization, jagged contours, over smoothing, imperfect reconstruction, etc. Image magnification in imaging applications requires interpolation to "read between the pixels". An output image of greater size preserving the information content as the original picture can be obtained by general techniques such as bilinear, bicubic interpolation or replication. But these techniques do not achieve the visual sharpness of the image. The goal of our work was to propose a prototype for image up scaling that preserves the quality of the image with "natural texture" and to reduce the computation time. The problem is to represent an image on a large bitmap from original data sampled in a smaller grid preserving the relevant image features and natural texture.

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IV. PROPOSED SYSTEM METHODOLOGY

A. Objective of the proposed System

Image magnification generally results in loss of image quality. Therefore image magnification requires interpolation to read between the pixels. Generally the enlarged images suffer from imperfect reconstructions, pixelization and jagged contours. The proposed system provides error-free high resolution for real images. The basic idea behind the system comprises two basic steps:

- Fast Curvature Based Interpolation (FCBI) which involves the filling of missing values after zooming and Iterative
- Curvature Based Interpolation (ICBI) which involves the modification of the filled values. The results obtained from the simulation shows that the proposed interpolation algorithm improves the quality of the image both subjectively and objectively compared to the previous conventional techniques.

B. Basic approach of system design

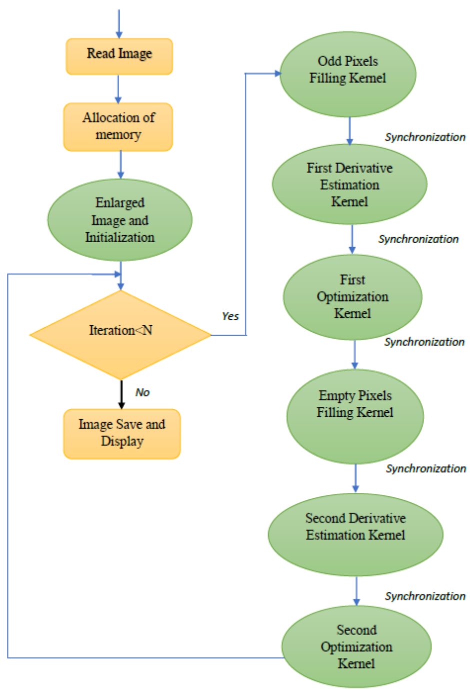

Fig .1. Flow chart representing the execution of the Interpolations

V. IMPLEMENTATION OF INTERPOLATIONS

A. Fast Curvature Based Interpolation (FCBI)

The method is similar to the Data Dependent Triangulation, but instead of obtaining the new pixel values by averaging the two opposite neighbors with lower difference, we compute second order derivatives in the two diagonal directions and interpolate the two opposite neighbors in the direction where the derivative is lower. In detail, if we consider the first interpolation step, we compute the local approximation of the second order derivative $I_{11}(2i+1,2j+1)$ and $I_{22}(2i+1,2j+1)$ along the two diagonal directions using a 12 pixel neighborhood as:

$$I_{11}(2i+1,2j+1) = I(2i-2,2j+2) + I(2i,2j) + I(2i+2,2j-2)$$
$$-3I(2i,2j+2) - 3I(2i+2,2j) + I(2i,2j+4) + I(2i+2,2j+2) + I(2i+4,2j) \quad (7)$$

$$I_{22}(2i+1,2j+1) = I(2i,2j-2) + I(2i+2,2j) + I(2i+4,2j+2)$$
$$-3I(2i,2j) - 3I(2i+2,2j+2) + I(2i-2,2j) + I(2i,2j+2) + I(2i+2,2j+4) \quad (8)$$

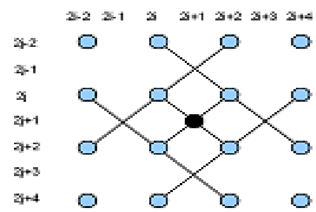

Fig .2. Edge-based interpolation based on a 12-pixels neighborhood: the largest second order diagonal derivative determines the interpolation direction.

The second step is performed in the same way, computing the approximations of the second order derivatives in horizontal and vertical directions. We only avoid the use of this simple rule when first order derivatives of the intensity are larger than a fixed, large threshold (in this case the derivative is not a good approximation of directional curvature). In this case we interpolate in the direction with lower gray level difference. Images obtained with this fast method are better than those obtained with similar fast edge directed methods, but not comparable, for example, with that obtained with improved NEDI. We therefore improved the algorithm by adding an iterative refinement able to improve edge quality at each interpolation step by smoothing second order directional derivatives keeping original pixel values fixed and adding constraints to preserve sharp discontinuities. The procedure is motivated by the fact that it is easy to derive, from NEDI equations, that one of the effects of the constant covariance constraint is, in case of limited intensity differences, to impose local continuity in second order derivatives of the intensity itself.

B. Curvature Based Interpolation (ICBI)

Let us describe the algorithm in details. The two filling steps, as written before, are performed by first initializing the new values with the FCBI algorithm, i.e., for the first step, computing local approximations of the second order derivative I_{11} (2i+1, 2j+1) and I_{22} (2i+1, 2j+1) along the two diagonal directions using eight valued neighboring pixels

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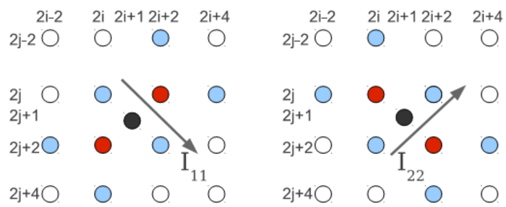

Fig .3. The average of the two neighbors in the direction of lowest second order derivative (I_{11}or I_{22}).

$$I_{11}(2i+1,2j+1) = I(2i-2,2j+2) + I(2i,2j) + I(2i+2,2j-2) -3I(2i,2j+2) - 3I(2i+2,2j) + I(2i,2j+4) + I(2i+2,2j+2) + I(2i+4,2j) \quad (9)$$

$$I_{22}(2i+1,2j+1) = I(2i,2j-2) + I(2i+2,2j) + I(2i+4,2j+2) -3I(2i,2j) - 3I(2i+2,2j+2) + I(2i-2,2j) + I(2i,2j+2) + I(2i+2,2j+4) \quad (10)$$

The point (2i+1, 2j+1) the average of the two neighbors in the direction where the derivative is lower. Interpolated values are then modified in an iterative procedure trying to minimize an "energy" function. This function is obtained by adding a contribution for each interpolated pixel, depending on the local continuity of the second order derivatives and on other quantities that are minima when desired image properties are reached. The sum of these pixel components should be minimized globally by varying the interpolated pixel values. It is clear that the computational cost of the procedure could be high. We apply, however, a greedy strategy just iterating the local minimization of each pixel term. Being the initial pixel value guess obtained with FCBI reasonable, the procedure leads quickly to a local minimum that appears to be reasonable for our task. We said that the main energy term defined for each interpolated pixel should be minimized by small changes in second order derivatives. For the first interpolation step (filling gaps in the enlarged grid at locations (2i+1, 2j+1)), we defined this term as

$$U_c(2i+1,2j+1) =$$

$$\omega_1(|(I_{11}(2i,2j) - I_{11}(2i+1,2j+1)| + |(I_{22}(2i,2j) - I_{22}(2i+1,2j+1))|) +$$

$$\omega_2(|I_{11}(2i,2j) - I_{11}(2i+1,2j-1)| + |(I_{22}(2i,2j) - I_{22}(2i+1,2j-1))|) +$$

$$\omega_3(|(I_{11}(2i,2j) - I_{11}(2i-1,2j+1))| + |(I_{22}(2i,2j) - I_{22}(2i-1,2j+1))|) +$$

$$\omega_4(|I_{11}(2i,2j) - I_{11}(2i-1,2j-1))| + |I_{22}(2i,2j) - I_{22}(2i-1,2j-1)|) \quad (11)$$

This energy term sums local directional changes of second order derivatives. Weights w are set to 1 when the first order derivative in the corresponding direction is not larger than a threshold T and to 0 otherwise. In this way smoothing is avoided when there is a strong discontinuity in the image intensity. Assuming that the local variation of the gray level is small, second order derivatives can also be considered an approximation of the intensity profiles curvature. This is why we call this term a "curvature smoothing" term, and defined the algorithm "Iterative Curvature Based Interpolation" (ICBI). The optimization procedure minimizing the sum of the curvature smoothing terms is really effective in removing artifacts, but tends to create over smoothed image. The smoothing effect can be only slightly reduced by replacing the second order derivative estimation with the actual directional curvature.

Image interpolation addresses the problem of generating a high-resolution image from its low-resolution version. The model employed to describe the relationship between high-resolution pixels and low-resolution pixels plays the critical role in the performance of an interpolation algorithm. Conventional linear interpolation schemes (e.g., bilinear and bicubic) based on space-invariant models fail to capture the fast evolving statistics around edges and consequently produce interpolated images with blurred edges and annoying artifacts. Linear interpolation is generally preferred not for the performance but for computational simplicity

VI. PSNR ESTIMATION TECHNIQUE

Image denoising or improving the visual quality of a digital image can be subjective. Saying that one method provides a better quality image could vary from person to person. For this reason, it is necessary to establish quantitative or empirical measures to compare the effects of image enhancement algorithms on image quality.

PSNR is most easily defined by the mean squared error (MSE). Given a noise free m×n monochrome image I (i, j) and its noisy approximation K (i, j), MSE is defined as the mean squared error (MSE) between two images I (i, j) and K (i, j)

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad (12)$$

Thus, MSE is the square of the difference between the two images, where m and n are the number of pixels of the two images respectively.

PSNR avoids many problem of measuring image quality by scaling the MSE according to the image range. It is defined by the equation

$$PSNR = -10\log_{10}\left(\frac{MSE}{s^2}\right) = 10\log_{10}\left(\frac{s^2}{MSE}\right) \text{ in dB} \quad (13)$$

where, S is the maximum pixel value. PSNR is measured in decibels (dB). The PSNR measure is also not ideal, but is in common use. Its main failing is that the signal strength is estimated as s^2, rather than the actual signal strength for the image.

In the absence of noise, the two images I (i, j) and K (i, j) are identical, and thus the MSE is zero. In this case the PSNR is undefined. Where I (i, j) is enlarged image and K (i, j) is original image.

A. PSNR Test Result

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ZF =2		ZF = 4	
FCBI	ICBI	FCBI	ICBI
28.444	30.085	22.210	23.833
27.082	28.721	21.249	22.371
29.585	30.826	24.032	24.937
30.512	31.908	24.795	25.737
27.453	29.094	21.265	22.566
30.316	32.377	23.483	24.986
29.213	30.673	23.491	24.558
31.380	33.523	24.656	26.041
37.147	38.838	30.950	31.982
31.216	32.110	26.569	27.176
32.627	33.695	27.554	28.149
35.238	36.657	29.060	30.401
27.551	28.163	23.466	24.149
32.196	32.550	28.812	29.254
27.818	29.070	22.532	23.232
32.106	33.321	26.885	27.497
30.129	31.281	24.781	25.481
30.530	31.531	25.396	25.897
29.410	31.340	22.966	24.115
28.627	29.494	23.963	24.514
29.783	30.570	25.338	25.911
23.608	24.535	19.000	19.736
29.653	30.872	24.459	25.543
27.082	28.092	22.369	22.948
26.653	27.527	21.864	22.728

Table. 1 Comparison of Interpolation Techniques

Black and White images and enlarged them by a 4× factor with two different algorithms (FCBI, ICBI). The sum of the successful comparisons for each interpolation method was then taken as the quality score of the method itself. The image quality PSNR and time performances obtained with the ICBI algorithm varying the maximum number of iterations. It is possible to have a PSNR close to the best one obtained. With more than iterations the difference in PSNR becomes negligible It should also be noted that optimizing methods in order to achieve maximum PSNR is not necessarily the best thing to do to have very good images, being PSNR not necessarily corresponding to visually perceived quality. For example, using ICBI we found that the PSNR values can be increased by adding more weight to the sharpening term, but at the cost of creating visible artifacts.

B. Time Calculations for ICBI and FCBI

TIME ICBI	TIME FCBI
3.479 sec	0.062 sec
7.098 sec	0.109 sec
10.546 sec	0.156 sec
13.603 sec	0.218 sec
18.174 sec	0.281 sec
21.575 sec	0.328 sec
24.695 sec	0.374 sec
28.252 sec	0.437 sec
30.545 sec	0.484 sec
33.181 sec	0.546 sec
35.303 sec	0.608 sec
37.362 sec	0.655 sec
39.952 sec	0.718 sec
41.917 sec	0.780 sec
44.866 sec	0.889 sec
47.393 sec	0.952 sec
50.045 sec	1.061 sec
52.448 sec	1.108 sec
56.067 sec	1.154 sec
58.906 sec	1.201 sec
61.449 sec	1.279 sec
65.177 sec	1.326 sec
68.765 sec	1.388 sec
71.870 sec	1.498 sec
75.130 sec	1.560 sec

Table. 2 Time calculations of Interpolation Techniques

We created 128 × 128and 256 × 256subsampled versions of the original images and the down sampled reference images. Different classes of algorithms required different reference images to compensate the slightly different zoom factors and translation created by the algorithms. We applied the exact or approximate 2×enlargement to the 256×256images and the 4×enlargement to the 128×128 ones. Finally we measured the differences between the up-scaled images. Computation times reported in tables are obtained with non-optimized MATLAB Implementations.

VII. RESULTS AND DISCUSSIONS

Here we are taken the Black & White and color Digital images of the image sizes are the 128x128, 256x256,

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512x512.In this digital images we are applying the ICBI method the output image size will be increased and this output will be high quality of the original image.

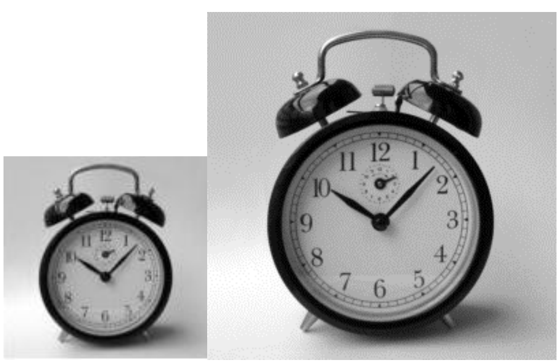
A. Comparison of ICBI and FCBI

(a1) (a2)

Fig 4. (a1) Input image and Fig. 4(a2) Out Put Image ICBI Method

(b1) (b2)

(c1) (c2)



(d1) (d2)

(e1) (e2)

Fig 5. (b1), (c1), (d1), (e1) Input Images, Fig. 5. (b2), (d2) Output Images of ICBI and Fig 5. (c2), (e2) Output Images of FCBI

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Fig 6. (f1), (g1), (h1), (i1), (j1), (k1) Input Images, Fig. 6. (f2), (h2), (j2), (l2) Output Images of ICBI Method and Fig 6. (g2), (i2), (k2), (m2) Output Images of FCBI

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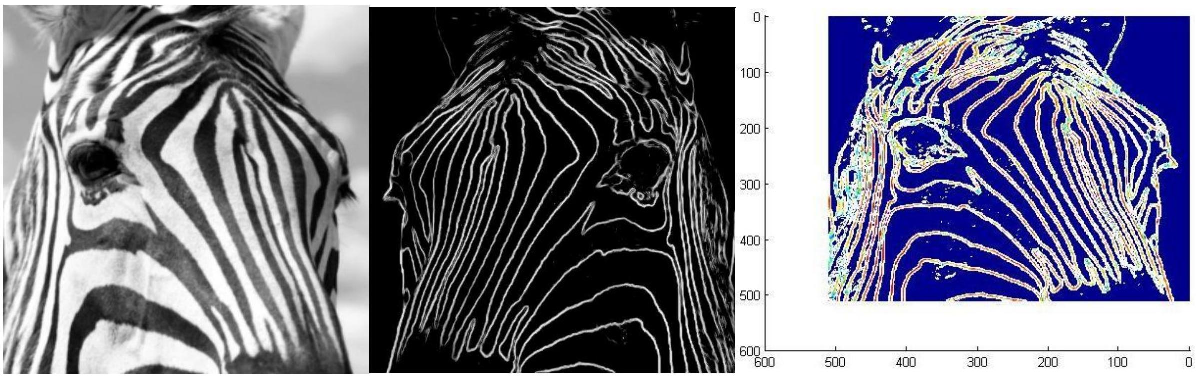
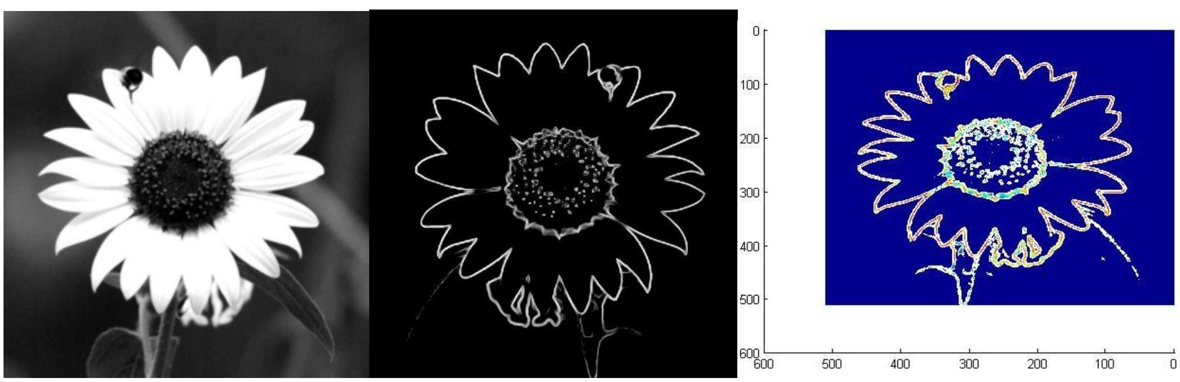
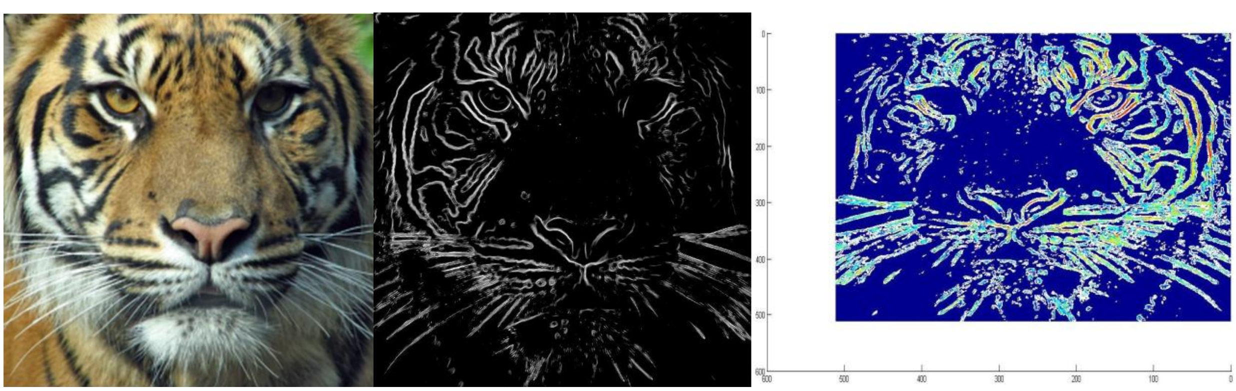
B. Edge Test Results



(n1) (n2) (n3)



(o1) (o2) (o3)



(p1) (p2) (p3)

Fig 7. (n1), (o1), (p1): Input Images, Fig 7. (n2), (o2), (p2): source images (grayscale) and Fig 7. (n3), (o3), (p3) EDGE: edge strength images

This function detects edges, which are those places in an image that correspond to object boundaries. To find edges, this function looks for places in the image where the intensity changes rapidly, using an improved. This implementation is not intended to be used in a production environment. The main purpose of this script is to clearly show how this technique works. Better performances could be obtained using a compiled version or rewriting this technique using a low-level programming language.

This detects the angles of the tangents to image edges. Angles are counted counter-clockwise starting from horizontal. The edges are those places in an image that correspond to object boundaries

VII. CONCLUSION

We implemented the ICBI algorithm by creating several steps of the algorithm using kernels. In this way computation performed in different blocks of the image can be executed in parallel, while the execution of the different steps is synchronized. With this implementation, we obtained the 4× enlargement of 128×128 color images in 16.2 ms on average, and the 2× enlargement of 256 × 256 images in 12.3ms on average and obtaining the same image quality using ICBI Method (i.e. PSNR=30.085 dB for ZF=002, PSNR=23.833dB for ZF=004) but FCBI have less quality images (i.e. PSNR=28.444dB for ZF=002, PSNR=22.210dB for ZF=004). With this we conclude that ICBI is very efficient compared to FCBI. This example implementation clearly shows the possibility of applying ICBI for real time applications and it is implemented using MATLAB Software Programming Language.

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