

IMPLEMENTATION OF IMAGE ENHANCEMENT SYSTEM WITH CONSTRAINT-BASED INTERPOLATION ALGORITHM

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ABSTRACT

Constraint-Based Interpolation Algorithm estimates the sampling functions found in cameras and analyzes properties of real world images in order to produce quality real-world image magnification. Performing image interpolation increases the resolution by a specified zoom factor. Image reconstruction is the process of converting a sampled image into a continuous one prior to transformation and resampling. To accomplish this, we purpose Constraint-Based Interpolation algorithm that uses a sensor model to push the pixels in an interpolation to more closely match the data in the sampled image. Real-world image properties are ensured with a level-set smoothing model that smooth “sharpening” and a sharpening model that alleviates blurring. The proposed qualitative and quantitative analysis provides robust and high magnification scale values.

Keywords: Digital image processing, image magnification, interpolation, Constraint-Based Interpolation Algorithm.

1. INTRODUCTION

Today, there is a huge amount of digital images available to computer user. This is caused by the rapid growth both in computer hardware and software technologies. The significant development in the field of computer graphics has also boosted the production of digital image. This is particularly important for desktop publishing, large artistic printing, etc. The problem is that high-resolution images are not usually provided. In these cases,

there is a need to magnify the original images. Therefore, the development of a good image magnification algorithm is very important. Image interpolation is becoming an increasingly important topic in digital image processing, especially as consumer digital photography is becoming ever more popular. From enlarging consumer images to creating large artistic prints, interpolation is at the heart of it all.

2. RELATED WORK

A. Murat TEKALP, Mehmet K.OZKAN and M. Ibrahim SEZAN [1] presented the problem of reconstruction of a high-resolution image from number lower resolution (possibly noisy) frames of the same scene. They showed that the POCS formulation presented for the high resolution image reconstruction problem could also be used as a new method for the restoration of spatially variant blurred images.

Muhammad Sajjad, et.al, proposed a new adaptive interpolation technique for digital image magnification for gray scale and color image. They calculated threshold, classify interpolation region in the form of geometrical shapes and then assign suitable values inside interpolation region to the undefined pixels while preserving the sharp luminance variations and smoothness at the same time [12].

This paper [3] presented a method for constrained smoothing of such artifacts that attempts to produce smooth reconstructions of the image’s level curves while still maintaining image fidelity.

3. THEORETICAL BACKGROUND

Interpolation is the estimation of values in a function between known points. Many algorithms

have been created to interpolate high-resolution images. There are several general approaches that these algorithms take, including function-fitting, filter-based, and edge-directed. More sophisticated inter-polating functions and non-exact fitting of the data can be used, but the idea is the same best-fit functions. To consider all possible interpolation during magnification algorithm and assign a suitable value to the undefined pixel is very important.

3.1. Pixel Replication

Pixel replication is far the simplest and fastest function fitting method. In order to estimate the unknown pixels in the high resolution grid, it simply uses the value of the nearest neighbor, or in other words, the closest original pixel value. Hence the higher resolution image is blocky and jagged, since the original pixels have “grown” by exactly the magnification scale. However, the resulting magnified images have aliasing effect in the form of jagged edges.

3.2. Bilinear Interpolation

Bilinear Interpolation fits a piecewise linear function between known pixel values. Bilinear Interpolation determines the value of a new pixel based on a weighted average of the 4 pixels in the nearest 2x2 neighborhood of the pixel in the original image [9]. Bilinear Interpolation produces magnifications that are more visually appealing than pixel replication.

3.3. Edge-directed Interpolation

The base idea of Edge-Directed Interpolation techniques is to analyze edge information in the low-resolution image in order to aid in the interpolation step. Edge information can be used in a variety of ways whether to interpolate in the edge direction or not allow interpolations to cross edges [10].

4. CONSTRAINT-BASED INTERPOLATION

Constraint-Based Interpolation utilizes several techniques to create realistic interpolations of

images. By analyzing general properties of real-world images, several models have been implemented to ensure that an interpolation creates an image that maintains these properties. This section explains the framework of the Constraint-Based Interpolation algorithm in its entirety. Each step is explained, including the initial interpolation and the iterative process of the sensor, smoothing, and sharpening models. The Constraint-Based Interpolation algorithm is implemented in order to help ensure that image magnifications stayed true to general characteristics of real-world images.

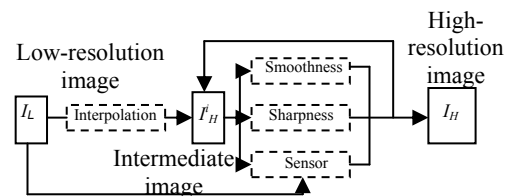


Figure 1. Constraint-Based Interpolation Framework

The first step of the algorithm is to generate an image that is an initial approximation to the correct high-resolution reconstruction. The iterative step corrects the image to the desired result. In each iteration, the current intermediate image is given to the sensor, smoothing, and sharpening models. Each of these models then saves data about how much they would like each pixel in the image to change. The last step of the iteration involves combining the three models’ information and creating a new intermediate image. To accomplish this, each models is given a user-defined weight determining how much force each model is able to exert on the intermediate image. This iteration is continued until a user-specified number of iterations have lapsed. The most recent intermediate image then becomes the final higher-resolution image.

4.1. Initial Interpolation

The first step of the Constraint-Based Interpolation algorithm is to perform an initial interpolation. The closer initial interpolation, the less iterations that are needed to correct errors in the interpolation. The Quad-Based Interpolation is based on quadrilaterals that best fit the gradient direction,

instead of using straight interpolation between pixels found to be partners using the gradient direction [4]. This algorithm is also similar to data dependent triangulation [16] but instead of arbitrary triangles we use a small set of predetermined quadrilaterals and use a simple difference cost function based on gradient direction as shown in Fig 2.

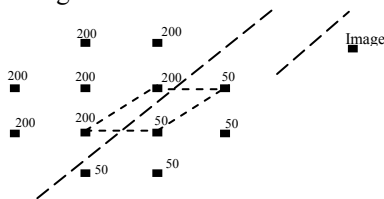


Figure 2. Quadrilaterals are Chosen Based on Edge Information

It consists of three steps. First, the gradient direction is calculated for every low resolution pixel. Next, for every 2x area in the high resolution grid, we analyze the nine quadrilateral candidates to find the best fit of the gradient direction. The nine quadrilaterals pixel values are shown in Figure 3.

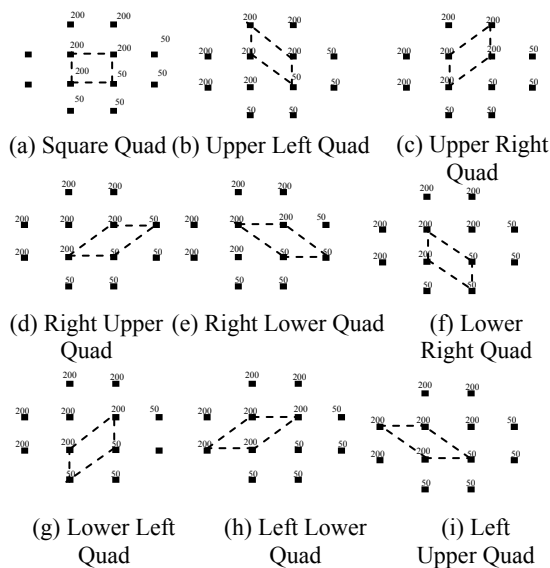


Figure 3. The Nine Possible Quadrilateral Values in Quad-based Interpolation

The final step in the algorithm is to perform Bilinear Interpolation within the best-fit

quadrilateral. To accomplish this interpolation within the quadrilateral, only either the x or y percentages need to be updated from Standard Bilinear Interpolation.

4.2. Sensor Model

The sensor constraint ensures that the higher-resolution image that is produced is still consistent with the data in the low-resolution image. The sensor model is similar to other constraints proposed in related magnification work. This model attempts to make the magnification image-consistent, meaning that if the high resolution image is down sampled using the same sensor function used to acquire the low-resolution original, it would exactly match the original data.

The sensor model is also used to ensure that the smoothing and sharpening models do not change the higher-resolution image too drastically. The sensor model ensures that the area around every pixel matches the low-resolution data. First, a kernel is created in order to compute area averages. This kernel is then passed over the high-resolution image. A difference calculation is then performed for pixels that map exactly to low-resolution pixels.

This difference value is then spread over the high-resolution area by utilizing the same kernel weights. These values are used as the sensor model. In order to allow for arbitrary non-integer and non-uniform magnification scale values, this algorithm has to be modified. When an image is magnified by arbitrary magnification scale values, the high-resolution grid becomes distorted. For instance, in 2×3 magnification, the high-resolution grid no longer has the same aspect ratio as the low-resolution grid as shown in Figure 4.

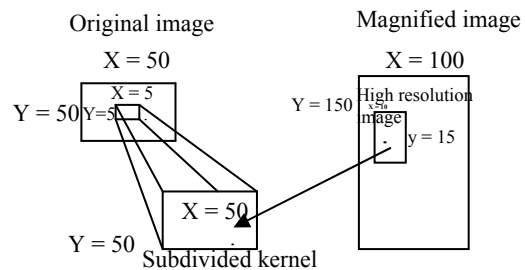


Figure 4. Sensor Model Bounding Box

4.3. Smoothing Model

The smoothness constraint attempts to smooth the contours in the image in order to remove what are known as the “sharpening”. Many interpolation techniques produce “sharpening” around edges, thus producing jagged level curves. However, real-life images generally have smooth level curves. Fortunately, explicitly finding the level curves in order to manipulate them is not necessary, since it has been shown that a level curve through a pixel can be moved by changing the intensity at that pixel. A flow equation can be used as a mechanism for this movement:

$$I_t = F \|\nabla I\| \quad (1)$$

Where,

F = the speed of movement of the level curve

∇I = changing the intensity at each pixel

I_t = pixel intensity

By using the negative isophote curvature $-k$ as the speed F , level curves contract at a rate proportional to their curvature places of high curvature contract more quickly than smoother parts of the curve.

$$I_t = -k \|\nabla I\| \quad (2)$$

Where,

k = negative isophote curvature

∇I = changing the intensity at each pixel

Calculation of the isophote curvature k similarly does not require explicit representation of the level curve. It can be calculated from local derivatives of the intensity [2].

$$\kappa = \text{div}(\nabla I / \|\nabla I\|) = -\frac{I_x^2 I_{yy} - 2I_x I_y I_{xy} + I_y^2 I_{xx}}{(I_x^2 + I_y^2)^{3/2}} \quad (3)$$

Where,

∇I = changing the intensity at each pixel

k = negative isophote curvature

I_x = pixel intensity of x direction

I_y = pixel intensity of y direction

4.4. Sharpening Model

As can be seen in real-life images, most edges are sharp and smooth. Using this qualitative prior, can know high-resolution magnification should also have sharp edges. The general idea of shock filters is to change pixel intensities to be closer to those of

pixels in the direction away from edges. The general form of the shock equation is given as follows:

$$I_t = -F(I_{ww}) \|\nabla I\| \quad (4)$$

Where,

F = function of I_{ww} used in various implementations

∇I = changing the intensity at each pixel

I_t = pixel intensity

I_{ww} = cross contour curvature

The function of I_{ww} used in various implementation of the shock equation to control the flow of the filter. In the implementation of the shock filter, use the following equation:

$$I_t = -\nabla \|\nabla I\| \cdot \nabla_{\text{upwind}} I \quad (5)$$

Where,

∇I = changing the intensity at each pixel

I_t = pixel intensity

$\nabla_{\text{upwind}} I$ = changing the intensity of vector field

This equation, once analyzed, is mathematically equivalent to the general form of the shock equation where $F(I_{ww}) = I_{ww}$.

4.5. Overview of the Proposed System

The proposed System attempts to enhance the real world unclear image into a good resolution image by applying Constraint-Based Interpolation Algorithm. By analyzing general properties of real-world images, three models have been implemented to ensure that an interpolation creates an image that maintains these properties.

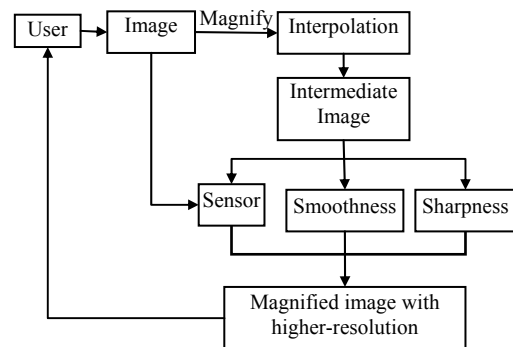


Figure 5. System Architecture of the Proposed System

Figure.5 shows that user magnify an image. To magnify the image, we must use the constraint-based interpolation method. The proposed method attempts to enhance the real world unclear image into a high resolution image. The proposed system used three models (Sharpness, Smoothness, Sensor). The interpolation with three models produced the magnified image with higher-resolution to the user.

5. ANALYSIS AND RESULT

For any image magnification algorithm to be considered successful, it needs to excel in both a qualitative and a quantitative analysis when compared with other magnification techniques. Result of the magnification can be seen in Figure.6. The image enhanced by constraint-based interpolation method preserves the sharpness and smoothness of the original approximation while reducing artifacts.

5.1. Qualitative Analysis

In qualitative analysis of proposed Interpolation comparison was made with series of image and was judge. By this one comparison the reader can judge for themselves if proposed Interpolation produces results that are superior to common magnification techniques.

5.2. Quantitative Analysis

It is difficult to rank a technique by just looking at its visual results. So there must be a mathematical method used to compare different underlying interpolation techniques. Proposed interpolation method can be compared with other interpolation algorithms like nearest neighbor (NN), bilinear (BL), bicubic (BC), level-set magnification. Three of the measurements reflect the accuracy of the magnification. These measurements are Mean Squared Error (MSE), Mean Absolute Error (MAE), and Cross Correlation Coefficient (CCC). The equations are given from 6 to 8.

$$ccc = \frac{\left[\sum_{x=1, y=1}^{M, N} \hat{I}(x, y)I(x, y) - n.a.b \right]}{\sqrt{\left(\sum_{x=1, y=1}^{M, N} \hat{I}^2(x, y) - na^2 \right) \left(\sum_{x=1, y=1}^{M, N} I^2(x, y) - kb^2 \right)}} \quad (6)$$

$$MSE = \frac{\sum_{x=1, y=1}^{M, N} (\hat{I}(x, y) - I(x, y))^2}{MN} \quad (7)$$

$$MAE = \frac{\sum_{x=1, y=1}^{M, N} |\hat{I}(x, y) - I(x, y)|}{MN} \quad (8)$$

Where

\hat{I} = the magnified image

I = the original image

n = the total number of pixels

a, b = the corresponding average pixel value in each image.

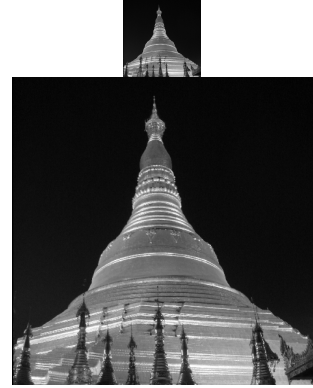


Figure 6. Result of the Magnification 4x with Proposed Method

6. CONCLUSION

The proposed system attempts to remove many of the artifacts that are predominant in standard magnification techniques. Common artifacts include blurring, ringing, and the sharpening, or jaggedness along edges in an image. These artifacts are removed in the algorithm by using level-set smoothing and sharpening models. By combining these three models, the Constraint-Based Interpolation algorithm is able to produce real-world magnifications that user studies show are preferred over magnifications produced by common magnification methods. The experimental results show that the proposed method while of not

greater complexity provide quantitatively and qualitatively good results.

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