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Image magnification by least squares surfaces

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Abstract

Image magnification is one of the current issues of image processing in which keeping the quality and structure of images is the main concern. In image magnification, it is necessary to insert information in extra pixels. Adding information to an image should be compatible with the image structure without making artificial blocks. In this research, extra pixels are estimated using the surface of least squares, and all the pixels are reviewed according to the suggested edge-improving algorithm. The suggested method keeps the edges and minimizes the magnified image opacity and the artificial blocks. Numerical results are presented by using PSNR and SSIM fidelity measures and compared to some other methods. The average PSNR of the original image and image zooming is 32.79 which it shows that image zooming is very similar to the original image. Experimental results show that the proposed method has a better performance than others and provides good image quality.

Keywords: Image Magnification; Least Squares Surface; Interpolation.

1 Introduction

Image magnification is, indeed, image resolution increasing to achieve a higher- quality image. It plays an important role in image processing and

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machine vision. Image magnification has various applications in electronic publishing industries, digital cameras, medical imaging, images on the web, license plate recognition, and face recognition systems in law functions.

Recent studies indicate that the main emphasis is on the visual quality of images in many applications. Resolution edges and lack of blur and additional artifacts are two important factors in image quality. Many enlarging image algorithms use interpolation methods. Interpolation means to find a set of unknown pixel values in a set of known pixel values in the picture. In magnification, the following few basic parameters affect the image quality [11]:
1- An efficient magnification method should preserve the edges and boundaries.
2- The method should not produce undesirable constant piecewise or blocks of other regions.
3- The magnification method should be computationally efficient but not too dependent on the internal parameters of the image.

Traditional technologies in image magnification use linear interpolation for high-resolution samples. Pixel replication, bilinear interpolation, quadratic interpolation, bi-cubic interpolation, and spline interpolation are some of these methods [6, 8, 17]. These methods tend to smooth edges or produce blocky interpolated images with staircase edges. Therefore, the output of these methods produces blurred images. This indicates the inability of linear technologies to transfer new information to an image.

One of the features of the two linear interpolation methods is that, in the magnification ratio, artificial blocks and visual effects are undesirable, but edges are preserved at an acceptable level. In bi-cubic interpolation method with a high zoom ratio, artificial blocks and undesirable visual effects are lower, and the edges are preserved. Although determining the image quality is not easy in this method, for image magnification, the quadratic interpolation is better than bilinear interpolation, bi-cubic interpolation is better than quadratic interpolation, and spline interpolation is better than bi-cubic interpolation [16].

In recent years, nonlinear interpolation methods have been used to reform linear methods for improving image quality and solving the blur problem. The change of non-linear methods depends on the interpolation method. This means that the performance of these methods with sharp edges is different from their performance on soft tissues, while linear methods with all the pixels act in the same way [1, 3, 7]. In order to maintain the image quality and edges in non-linear methods, estimation methods of a subset of edge pixels [1], resampling and optimization parameters, implicit interpolation, and straight edges have been used [4, 14, 22].

In [22], a statistical method that tunes interpolation coefficients according to local edge structures is proposed. The technique of [4] uses a modified bilinear method, where the interpolation error theorem in an edge-adaptive fashion.

In [21], an edge-directed nonlinear interpolation technique is presented through directional filtering and data fusion. This algorithm interpolates a missing pixel in multiple directions, and then fuses the directional interpolation results by linear minimum mean square-error estimation.

In [2], the local adaptive magnification (LAZ) method uses the discontinuities information or sharp brightness changes, finds edges in different directions by taking two threshold values, and estimates the unknown pixels with respect to the edge pixels.

In [20], the artificial neural networks methods uses for doing zoom operations on digital images.

In [10], presents a nonlinear image interpolation algorithm that is based on the moving least squares technique. This methods ability to image zooming and preserving edge features.

In this paper, another least squares surface method is suggested, in which necessary pixels are obtained by calculating their coefficients using the least squares theory and edge-directed algorithms.

This paper continues as follows. In the second part, quadratic surfaces and the theory of least squares will be discussed. In the third part, the least square planes, suggested algorithms, and evaluation parameters will be proposed. The fourth section compares the results of implementation by other methods. In the last section, conclusions and recommendations will be presented.

2 Quadratic surfaces and least squares theory

The purpose of a quadratic surface in R^3 space composed of x, y and z is formed as equation (1), in which none of the coefficients A, B, C, D, E and F is zero. This equation called quadratic surfaces is an extension of a cone in R^2 space.

$$Ax^2 + By^2 + Cz^2 + Dxy + Exz + Fyz + Gx + Hy + Iz + J = 0. \tag{1}$$

Without losing any generality, the coefficients of product terms can be zero by a three-dimensional rotation, and convert equation (1) into a conventional or canonical form by a transfer, whose diagram is recognizable. The canonical equation for a quadratic surface is as in (2), the most famous sections of which are elliptical, hyperbolic, parabolic, and conic sections.
For example, the overall shape of an elliptical equation and parabolic surface are introduced according to equations (3) and (4), respectively:

$$Ax^2 + By^2 + Cz^2 + Gx + Hy + Iz + J = 0 \tag{2}$$

$$Ax^2 + By^2 + Cz^2 + Gx + Hy + Iz = 1 \tag{3}$$

$$Ax^2 + By^2 + +Gx + Hy = Iz \tag{4}$$

2.1 Least Squares Theory

Suppose $f(x)$ is a continuous function on the $[a, b]$ interval and $p(x)$ is a polynomial of the maximum degree n that is defined according to equation (5), in which c_i constants for $i = 0, 1, 2, \ldots, n$ are real numbers.

$$p(x) = \sum_{i=0}^{n} c_i x^i. \tag{5}$$

The problem of approximating function f(x) by polynomial $p(x)$ can be considered by finding c_i constants for $i = 0, 1, 2, \ldots, n$ to minimize $||f(x) - p(x)||$. The purpose of $||.||$ is Euclidean norms. To calculate the coefficients of c_i, Theorem 1 is used.

Theorem 1. *Let $f(x_1, x_2, \ldots, x_n)$ be a function of n variables which has a local extremum at the point $(a_1, a_2, \ldots, a_n)$. Then either f is non- differentiable at $(a_1, a_2, \ldots, a_n)$, or it is differentiable at $(a_1, a_2, \ldots, a_n)$ and $\nabla f(a_1, a_2, \ldots, a_n) = 0$ or $\frac{\partial f}{\partial x_i}(a_1, a_2, \ldots, a_n) = 0, \quad i = 0, 1, 2, \ldots, n$*

If a set of data are in the form of $\{(x_i, y_i) \,|i = 1, 2, \ldots, N\}$ and the suitable mathematical model for data relationship is a line, then the general problem is finding the best least squares line. A mathematical model for the relationship of the data is the polynomial of degree n in general for which $n < N$., Then the problem is to find the least squares polynomial. Therefore, if the discrete data based on Euclidean norms are considered as in expression (6) according to Theorem 1, equation (7) should be established.

$$E = \sum_{i=1}^{N} \left(y_i - (c_0 + c_1 x_i + \ldots + c_n {x_i}^n)\right)^2 \tag{6}$$

$$\frac{\partial E}{\partial c_j} = 0, \quad j = 0, 1, 2, \ldots, n. \tag{7}$$

After calculating the partial derivatives and simplifying them, the linear system of $(n + 1)$ equations called normal form is obtained as in (8) for distinct x_i, for $i = 1, 2, \ldots, N$. This linear system of equations has a unique solution.

$$\begin{cases} c_0\sum_{i=1}^{N} x_i^0 + c_1\sum_{i=1}^{N} x_i^1 + \ldots + c_n\sum_{i=1}^{N} x_i^n = \sum_{i=1}^{N} y_i x_i^0 \\ c_0\sum_{i=1}^{N} x_i^1 + c_1\sum_{i=1}^{N} x_i^2 + \ldots + c_n\sum_{i=1}^{N} x_i^{n+1} = \sum_{i=1}^{N} y_i x_i^1 \\ \quad\vdots \qquad\qquad \vdots \qquad\qquad\qquad \vdots \qquad\qquad \vdots \\ c_0\sum_{i=1}^{N} x_i^n + c_1\sum_{i=1}^{N} x_i^{n+1} + \ldots + c_n\sum_{i=1}^{N} x_i^{2n} = \sum_{i=1}^{N} y_i x_i^n \end{cases} \tag{8}$$

If $f(x, y, z) = 0$ is a surface equation in the R^3 space, z depends on x and y. In addition, $\{(x_i, y_i, z_i)\,|i = 1, 2, \ldots, N\}$ is a set of discrete data obtained from the process of data collection, non of which lie on a known surface, either elliptical, or parabolic, or plane. Then according to 1 and the sum squares error, appropriate coefficients can be calculated.

Suppose $z = Ax + By + C$ is a surface equation in the R^3 space for $\{(x_i, y_i, z_i)\,|i = 1, 2, \ldots, N\}$ points. To obtain the surface of least squares Theorem 1 and error (9), the coefficients of A, B, C are calculated after solving normal equations (10).

$$E = \sum_{i=1}^{N} \left(Ax_i + By_i + C - z_i\right)^{2} \tag{9}$$

$$\begin{cases} A\sum_{i=1}^{N} x_i^2 + B\sum_{i=1}^{N} x_i y_i + C\sum_{i=1}^{N} x_i = \sum_{i=1}^{N} z_i x_i \\ A\sum_{i=1}^{N} x_i y_i + B\sum_{i=1}^{N} y_i^2 + C\sum_{i=1}^{N} y_i = \sum_{i=1}^{N} y_i z \\ A\sum_{i=1}^{N} x_i + B\sum_{i=1}^{N} y_i + C\sum_{i=1}^{N} 1 = \sum_{i=1}^{N} z_i. \end{cases} \tag{10}$$

If $Ax^2 + By^2 + Cx + Dy = 1 - z^2$ is an elliptical surface in the space R^3 and $\{(x_i, y_i, z_i)\,|i = 1, 2, \ldots, N\}$ points are provided, calculation of the elliptical least-squares surface can be done according to Theorem 1 and deviation (11), with coefficients A, B, C, D achieved after solving linear device (12).

$$E = \sum_{i=1}^{N} \left(Ax_i^2 + By_i^2 + Cx_i + Dy_i + z_i^2 - 1\right)^{2} \tag{11}$$

$$\begin{cases} A\sum\limits_{i=1}^{N} x_i^4 + B\sum\limits_{i=1}^{N} x_i^2y_i^2 + C\sum\limits_{i=1}^{N} x_i^3 + D\sum\limits_{i=1}^{N} y_ix_i^2 = \sum\limits_{i=1}^{N} x_i^2\left(1-z_i^2\right) \\ A\sum\limits_{i=1}^{N} x_i^2y_i^2 + B\sum\limits_{i=1}^{N} y_i^4 + C\sum\limits_{i=1}^{N} x_iy_i^2 + D\sum\limits_{i=1}^{N} y_i^3 = \sum\limits_{i=1}^{N} y_i^2\left(1-z_i^2\right) \\ A\sum\limits_{i=1}^{N} x_i^3 + B\sum\limits_{i=1}^{N} x_iy_i^2 + C\sum\limits_{i=1}^{N} x_i^2 + D\sum\limits_{i=1}^{N} y_ix_i = \sum\limits_{i=1}^{N} x_i\left(1-z_i^2\right) \\ A\sum\limits_{i=1}^{N} x_i^2y_i + B\sum\limits_{i=1}^{N} y_i^3 + C\sum\limits_{i=1}^{N} x_iy_i + D\sum\limits_{i=1}^{N} y_i^2 = \sum\limits_{i=1}^{N} y_i\left(1-z_i^2\right). \end{cases} \tag{12}$$

Similarly, if $Ax^2 + By^2 + Cx + Dy = z$ is parabolic surface in the space R^3 and $\{(x_i, y_i, z_i)\,|i = 1, 2, \ldots, N\}$ points are provided, calculation of the parabolic least-squares surface can be done according to Theorem 1 and deviation (13), with coefficients A, B, C, D achieved after solving linear device (14).

$$E = \sum_{i=1}^{N} \left(Ax_i^2 + By_i^2 + Cx_i + Dy_i - z_i\right)^2, \tag{13}$$

$$\begin{cases} A\sum\limits_{i=1}^{N} x_i^4 + B\sum\limits_{i=1}^{N} x_i^2y_i^2 + C\sum\limits_{i=1}^{N} x_i^3 + D\sum\limits_{i=1}^{N} y_ix_i^2 = \sum\limits_{i=1}^{N} x_i^2z_i \\ A\sum\limits_{i=1}^{N} x_i^2y_i^2 + B\sum\limits_{i=1}^{N} y_i^4 + C\sum\limits_{i=1}^{N} x_iy_i^2 + D\sum\limits_{i=1}^{N} y_i^3 = \sum\limits_{i=1}^{N} y_i^2z_i \\ A\sum\limits_{i=1}^{N} x_i^3 + B\sum\limits_{i=1}^{N} x_iy_i^2 + C\sum\limits_{i=1}^{N} x_i^2 + D\sum\limits_{i=1}^{N} y_ix_i = \sum\limits_{i=1}^{N} x_iz_i \\ A\sum\limits_{i=1}^{N} x_i^2y_i + B\sum\limits_{i=1}^{N} y_i^3 + C\sum\limits_{i=1}^{N} x_iy_i + D\sum\limits_{i=1}^{N} y_i^2 = \sum\limits_{i=1}^{N} y_iz_i. \end{cases} \tag{14}$$

Here, the linear equations system can be obtained for the quadratic surface.

3 Least Squares Surfaces and Image Magnification

In the image magnification, some new pixels are placed in the original pixels of the image. The purpose of magnification is to determine new pixels, which are determined based on their neighbouring pixels. There are two types of neighbourhood in two-dimensional images, which are known as the 4 and 8 cell. Neighbourhoods are shown in Figure 1.

In most of proposed methods, magnification rate is tried to be squared, or to a power of two, but it should be noted that the algorithm presented here is used for every magnification rate.

The first stage is the simplest one and requires expanding the source $n\times n$ pixels image onto a regular grid of size $(2n-1)\times(2n-1)$. More precisely, if

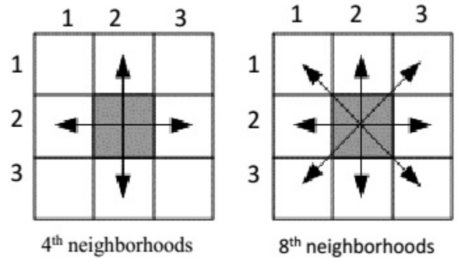

Figure 1: Types of neighbourhood.

$S(i,j)$ denotes the pixels in the i^{th} row and j^{th} column of the source image and $Z(l,k)$ denotes the magnified image pixel in the l^{th} row and k^{th} column in the zoomed picture, the f function [5] puts the original image pixel in the interlaced places of the new image:

$$f : S \to Z$$
$$f\left(S\left(i,j\right)\right) = Z\left(2i-1, 2j-1\right) \qquad i,j = 1,2,\ldots,n$$

The result is shown in Figure 2. The original image pixel is indicated by symbol $\bullet$, and the other pixels which must be estimated have been identified by $11, 10$ and 01. To estimate the pixel values, the multi-stage least squares method is used along with a review of the surfaces.

In this algorithm, a new pixel value is estimated with its four neighbourhoods in the corner (pixel 11) by the proposed method. Since, all the neighbourhoods on the central pixels are equal in term of distance from the central pixel, all of them are attributed the same weight. The results are shown in Figure 3, and $\blacksquare$ is replaced by the estimated pixels. In the next stage, the pixels indicated by 1 are estimated by their four neighbourhoods. These pixels have two main pixels in the left and the right and two estimated pixels up and down the neighbourhoods. In estimation, pixels that are indicated with number 01 have the weight of 1, and the estimated pixels assigned with the weight of 0.5. Pixels with number 10 are estimated in the same manner. The results are shown in Figure (4), in which the symbols $\square$ and $\diamondsuit$ are replaced by the estimated pixels.

3.1 Least squares surface algorithm

In this algorithm, a point ($\bullet$) refers to the pixel coordinates of the image whose brightness and number of rows and columns are considered as a point in a three-dimensional space.

•	01	•	01	•
10	11	10	11	10
•	01	•	01	•
10	11	10	11	10
•	01	•	01	•

Figure 2: Copying value to the magnified image.

•	01	•	01	•
10	▪	10	▪	10
•	01	•	01	•
10	▪	10	▪	10
•	01	•	01	•

Figure 3: Estimation of neighbourhood pixels.

•	□	•	□	•
◇	▪	◇	▪	◇
•	□	•	□	•
◇	▪	◇	▪	◇
•	□	•	□	•

Figure 4: Estimation of neighbourhood pixels.

To estimate the required pixels in image magnification based on four neighbourhoods, initially by selection the four points and solving the linear least-squares surface equation, the desired pixel is estimated. It should be noted that, two adjacent pixels are used in the rows and columns of pixels to approximate the first and last of the average.

The proposed algorithm steps are as follows:

Step 1. Establish a linear system according to the chosen least-square surface.

Step 2. Solve linear equations and calculating surface coefficients.

Step 3. Estimate the desired pixel by replacing the number of rows and columns on the selective surface.
Step 4. Repeat steps 1 to 3 in three stages according to the zooming algorithm and estimating the required pixel
Step 5. Review all the estimated pixels based on the conducted sub-algorithm of the edge (3-2).

3.2 The modified sub-algorithm of the image edges

After estimating all the required image pixels, all estimated pixels are reviewed to improve the edges (Figure.5) based on the following conditions. A, B, C, and d are the main pixels, and $X, Y2, Y1, Z1$, and $Z2$ are the estimated pixels. The advantage of the sub-algorithm is the lack of any provinces for edges. The proposed algorithm steps are as follows:
Step 1. If $|A - D| > |B - C|$, then $X \leftarrow \frac{B+C}{2}$. In fact, the edge is in the northeast-southwest direction.
Step 2. If $|A - D| < |B - C|$, then $X \leftarrow \frac{A+D}{2}$. In fact, the edge is in the northwest-southeast direction.
Step 3. If $(A - D)(B - C) > 0$, then $Y1 \leftarrow \frac{A+B}{2}$ and $Y2 \leftarrow \frac{C+D}{2}$. In fact, the edge is in the north-south direction.
Step 4. If $(A - D)(B - C) < 0$, then $Z1 \leftarrow \frac{A+C}{2}$ and $Z2 \leftarrow \frac{B+D}{2}$. In fact, the edge is in the west-east direction.

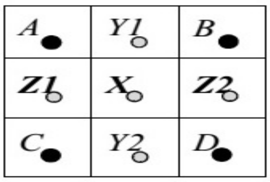

Figure 5: Design for modifying the image edge.

3.3 Assessment criteria

To compare two images in terms of their similarity, PSNR and SSIM criteria are used. The PSNR value is bigger and the SSIM is closer to 1, the images have more conformity [18, 19]. The PSNR criterion is calculated based on equation (15) and (16):

$$PSNR = 10 * Log_{10}\left(\frac{MAX_I^2}{MSE}\right)(dB) \tag{15}$$

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I(i,j) - K(i,j)\right]^2 \tag{16}$$

where $I(i,j)$ and $K(i,j)$ are the main image pixels and the estimated image, respectively, and MAX_I is the maximum image pixles.
SSIM criterion, which includes the image structural elements and measures the structural quality of the image as well as the similarity between the two images, has a value between 0 and 1. This means that 1 is the highest and 0 is the lowest similarity, which is calculated by equation (17).

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)} \tag{17}$$

where μ , σ^2 and σ_{xy} are the average, variance, and covariance of the pixels in the image, respectively, and c_1 and c_2 are two unknown constants that prevent the fraction denominator from being zero.

4 Simulation results

To evaluate the proposed method, first, a digital image is considered as an original image, and then its size is reduced by removing alternative rows of columns by half, then, it is tried to make image size double using the proposed method and the other methods. As expected, the closer the degree of similarity is to the original image size, the algorithm has a better performance.

Implementation of the results of the suggested algorithm done in MATLAB. The results are presented in Tables 1 and 2. In Table 1, the PSNR criterion is used for zooming, and ten different and standard images [15] are applied according to Figure 6. Their dimensions all are 512×512. The results of the suggested least square plane (LSP) and least square ellipsoid (LSE) methods, bilinear interpolation (BIL) method, bi-cubic interpolation (BIC) method, and curvature interpolation (CIM) method [9] have been compared. The least difference of PSNR between LSP method and CIM method is 0.38, the most is 3.18, and its average is 1.71. Comparing LSE with CIM and PSNR scale, the minimum difference is 0.13, the maximum is 3.12, and the average is 1.52. With regard to each row and comparing the results, it can be concluded that the proposed method of LSP has a better performance than other methods on the selected image.

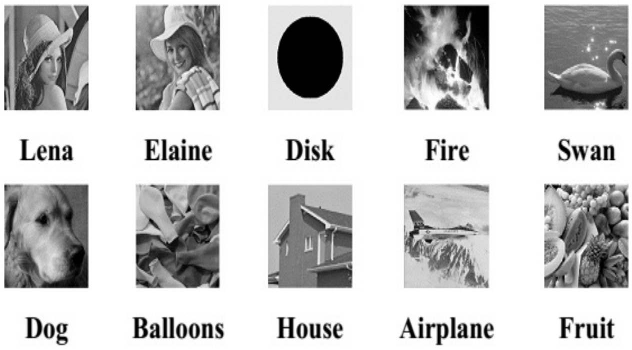

Figure 6: Different images and standards for image magnification.

Table 2 illustrates the results of comparing the suggested method and the other methods for the images in Figure 6, by SSIM criterion. The results show that the proposed method has a better performance than other methods with a good approximation. The minimum difference in SSIM for LSP by CIM is 0.0011, the maximum is 0.02, and the average is 0.0096. In a comparison of LSE method with CIM and SSIM criterion, the minimum difference is 0.001, the maximum is 0.099, and the average is 0.0095.

From a visual point of view, for example, the magnified image of Elaine is shown by LSP and LSE proposed methods, by BIL, BIC methods, as well as CIM method in Figure 7. Obviously, the images of the proposed method are more transparent and have less blur and good performance on the edges.

Figure 7: The results of Elaine's image magnification by the factor of 2 and using different methods.

Table 1: Comparison of the least square surface method and other methods by PSNR criterion.

Methods	BIL	BIC	CIM	Proposed method LSP	Proposed method LSE
lena	30.20	30.11	30.58	**33.47**	**33.34**
Elaine	31.26	31.08	31.49	**34.67**	**34.61**
Disk	30.94	30.82	31.56	**33.07**	**32.70**
Fire	31.66	31.71	31.82	**32.20**	**31.95**
Swan	31.19	30.74	31.44	**33.22**	**32.73**
Dog	31.83	31.37	32.05	**33.94**	**33.63**
Balloons	31.29	31.73	32.28	**33.52**	**34.07**
House	32.64	32.60	32.97	**34.00**	**33.83**
Airplane	29.70	29.59	30.12	**31.34**	**31.30**
Fruits	26.17	26.08	26.49	**28.44**	**28.20**
Average	30.69	30.58	31.08	**32.79**	**32.60**

Table 2: Comparison of the least square surface method and other methods by SSIM criterion.

Methods	BIL	BIC	CIM	Proposed method LSP	Proposed method LSE
lena	0.9504	0.9469	0.9514	**0.9714**	**0.9713**
Elaine	0.9536	0.9479	0.9578	**0.9589**	**0.9588**
Disk	0.9908	0.9908	0.9922	**0.9956**	**0.9953**
Fire	0.9770	0.9767	0.9779	**0.9857**	**0.9854**
Swan	0.9737	0.9727	0.9758	**0.98420**	**0.9841**
Dog	0.9701	0.9691	0.9708	**0.9814**	**0.9813**
Balloons	0.9815	0.9808	0.9856	**0.9893**	**0.9894**
House	0.9771	0.9763	0.9777	**0.9867**	**0.9866**
Airplane	0.9698	0.9696	0.9703	**0.9831**	**0.9831**
Fruits	0.9518	0.9513	0.9523	**0.9714**	**0.9712**
Average	0.9696	0.9682	0.9712	**0.9808**	**0.9807**

5 Conclusion

In this paper, a new method of the least squares surface has been used to enlarge images. Despite simple implementation and low computational complexity, this method provides more satisfactory results than bilinear interpolation methods, such as bicubic and curvature do. The study, has been conducted using one of the edge- improving techniques. The proposed method can be elaborated on in future studies through other edge- improving methods or nonlinear methods such as bivariate interpolation or radial basis functions interpolation with edge- shaving techniques.

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بزرگ نمایی تصویر توسط رویه‌های کم‌ترین مربعات

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چکیده : بزرگ نمایی تصویر یکی از مسائل موجود در زمینه پردازش تصویر است که مسئله اصلی در آن، حفظ کیفیت و ساختار تصویر بزرگ نمایی شده می‌باشد. در بزرگ نمایی لازم است که پیکسل های اضافی در اطلاعات تصویر قرار داده شود. اضافه کردن اطلاعات به تصویر باید با بافت موجود در تصویر سازگار باشد و بلوک های مصنوعی ایجاد نکند. در این پژوهش با استفاده از روش رویه‌های کم‌ترین مربعات، پیکسل های مورد نیاز تخمین زده می شوند و بر اساس الگوریتم پیشنهادی بهبود لبه، مجددا تمام پیکسل‌ها مورد بازنگری قرار می‌گیرند. روش پیشنهادی لبه‌ها را حفظ می‌کند و ماتی و مصنوعات بلوکی تصویر بزرگ‌نمایی‌شده را به حداقل می‌رساند. جهت سنجش توانایی این روش، نتایج حاصل بر روی چند تصویر با روش های دیگر توسط معیار PSNR و SSIM مورد مقایسه و ارزیابی قرار گرفته است. میانگین PSNR مربوط به تصویر اصلی و بزرگ‌نمایی شده ۷۹/۳۲ می‌باشد که نشان می‌دهد تصویر بزرگ‌نمایی شده به تصویر اصلی شباهت زیادی دارد. نتایج آزمایشات نشان می‌دهد روش پیشنهادی از کارائی بهتری نسبت به دیگر روش‌ها برخوردار است و تصویر با کیفیت مطلوب فراهم می‌کند.

کلمات کلیدی : بزرگ نمایی تصویر؛ رویه کم‌ترین مربعات؛ درونیابی.