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Image Magnification based on the Human Visual Processing

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1. Introduction

Image magnification is among the basic image processing operations and has many applications in a various area. In recent, multimedia techniques have advanced to provide various multimedia data that were digital images and VOD. It has been rapidly growing into a digital multimedia contents market. In education, many researches have used e-learning techniques. Various equipments - image equipments, CCD camera, digital camera and cellular phone - are used in making multimedia contents. They are now widespread and as a result, computer users can buy them and acquire many digital images as desired. This is why the need to display and print them also increases (Battiato & Mancuso, 2001; Battiato et al., 2002).

However, such various images with optical industry lenses are used to get high-resolution. These lenses are not only expensive but also too big for us to carry. So, they are using the digital zooming method with the lenses to solve the problem. The digital zooming method generally uses the nearest neighbor interpolation method, which is simpler and faster than other methods. But it has drawbacks such as blocking phenomenon when an image is enlarged. Also, to improve the drawbacks, there exist bilinear interpolation method and the cubic convolution interpolation commercially used in the software market. The bilinear method uses the average of 4 neighborhood pixels. It can solve the blocking phenomenon but brings loss of the image like blurring phenomenon when the image is enlarged. Cubic convolution interpolation improved the loss of image like the nearest neighbor interpolation and bilinear interpolation. But it is slow as it uses the offset of 16 neighborhood pixels (Aoyama & Ishii, 1993; Candocia & Principe, 1999; Biancardi et al., 2002).

A number of methods for magnifying images have been proposed to solve such problems. However, proposed methods on magnifying images have the disadvantage that either the sharpness of the edges cannot be preserved or that some highly visible artifacts are produced in the magnified image. Although previous methods show a high performance in special environment, there are still the basic problems left behind. Recently, researches on Human vision processing have been in the rapid progress. In addition, a large number of models for modeling human vision system have been proposed to solve the drawbacks of

machine vision such as object recognition and object detection (Suyung, 2001). In the field of optical neural, many researches have been conducted in relation with physiology or biology to solve the problem of human information processing. Features of biological visual systems at the retinal level serve to motivate the design of electronic sensors. Although commercially available machine vision sensors begin to approach the photoreceptor densities found in primate retinas, they are still outperformed by biological visual systems in terms of dynamic range, and strategies of information processing employed at the sensor level (Shah & Levine, 1993). However, most of the retina models have focused only on the characteristic functions of retina by generalizing the mechanisms, or for researcher's convenience or even by one's intuition. Although such a system is efficient to achieve a specific goal in current environment, it is difficult to analyze and understand the visual scene of a human body. The current visual systems are used in very restricted ways due to the insufficiency of the performance of algorithms and hardware.

Recently, there are many active researches to maximize the performance of computer vision technology and to develop artificial vision through the modeling of human visual processing. Artificial vision is to develop information processing procedures of the human visual system based on the biological characteristics. Compared with the machine vision technology, it can be effectively applied to industry. By investing over 20 billion yen between 1997 and 2016, Japan is conducting research on the areas of machine intelligence, voice recognition and artificial vision based on the information processing mechanism of the brain. By the National Science Foundation (NSF) and the Application of Neural Networks for Industries in Europe (ANNIE), America and Europe are also conducting research on artificial vision, as well as artificial intelligence and voice recognition using the modeling of the brain's information processing (Dobelle, 2000).

This paper presents a method for magnifying images that produces high quality images based on human visual properties which have image reduction on retina cells and information magnification of input image on visual cortex. The rest of this paper is organized as follows. Section 2 presents the properties on human visual system and related works that have proposed for magnifying image. Section 3 presents our method that extracts the edge information using wavelet transform and uses the edge information base on the properties of human visual processing. Section 4 presents the results of the experiment and some concluding remarks are made in Section 5.

2. Related works and human visual processing

2.1 Related works

The simplest way to magnify images is the nearest neighbor interpolation by using the pixel replication and basically making the pixels bigger. It is defined by equation (1). However, the resulting magnified images have a blocking phenomenon (Gonzalez & Richard, 2001).

$$Z(i, j) = I(k, l), \quad 0 \leq i, j, \text{ integer} \\ k \equiv \text{int} \left[\frac{i}{2} \right], l \equiv \text{int} \left[\frac{j}{2} \right], \text{ where } Z(i, j) \text{ is a magnified image} \quad (1)$$

Other method is the bilinear interpolation, which determines the value of a new pixel based on a weighted average of the 4 pixels in the nearest 2×2 neighbourhood of the pixels in the original image (Gonzalez & Richard, 2001). Therefore this method produces relatively

smooth edges with hardly any blocking and is better than the nearest neighbor but appears blurring phenomenon. It is defined as equation (2).

$$\begin{aligned} Z(i, 2j) &= I(k, l), \quad Z(i, 2j+1) = \frac{1}{2}[I(k, l), I(k, l+1)] \\ Z(2i, j) &= I_i(k, l), \quad Z(2i+1, j) = \frac{1}{2}[I_i(k, l), I_i(k+1, l)] \end{aligned} \quad (2)$$

More elaborating approach uses cubic convolution interpolation which is more sophisticated and produces smoother edges than the bilinear interpolation. Bicubic interpolation uses a bicubic function using 16 pixels in the nearest 4×4 neighborhood of the pixel in the original image and is defined by equation (3). This method is most commonly used by image editing software, printer drivers and many digital cameras for re-sampling images. Also, Adobe Photoshop offers two variants of the cubic convolution interpolation method: bicubic smoother and bicubic sharper. But this method raises another problem that the processing time is too long due to the computation for the offsets of 16 neighborhood pixels (Keys, 1981).

$$f(x) = \begin{cases} (a+2)|x|^3 - (a+3)|x|^2 + 1, & 0 \leq |x| < 1 \\ a|x|^3 - 5a|x|^2 + 8a|x| - 4a, & 1 \leq |x| < 2 \\ 0, & \text{elsewhere} \end{cases} \quad \text{where } a=0, \text{ or } -1 \quad (3)$$

Recently, research on interpolation images taking into account the edges has gained much attention. (Salisbury et al., 1996) proposed methods that search for edges in the input images and use them to assure that the interpolation does not cross them. The problem is how to define and find the important edged in the input image.

Other edge-adaptive methods have been proposed by (Li & Orchard, 2001). The commercial software Genuine Fractals also used an edge adaptive method to magnify images, but the details of the algorithm are not provided. Currently, the methods presented in (Muresan & Parks, 2004) are the most widely known edge-adaptive methods. They can well enough avoid jagged edges, but have limitation that they sometimes introduce highly visible artifacts into the magnified images, especially in areas with small size repetitive patterns (Johan & Nishita, 2004).

In section 3, we will propose an efficient method by image reduction and edge enhancement based on the properties on human visual processing.

2.2 Human visual processing

In the field of computer vision, many researches have been conducted in relation with edge information to solve the problem of magnification. Image information received from retina in Human visual system is not directly transmitted to the cerebrum when we recognize it. This is why there are many cells playing in Human visual system (Bruce, 2002).

First, the visual process begins when visible light enters the eye and forms images on the retina, a thin layer of neurons lining the back of the eye. The retina consists of a number of different types of neurons, including the rod and cone receptors, which transform light energy into electrical energy, and fibers that transmit electrical energy out of the retina in the optic nerve. Second, The signals generated in the receptors trigger electrical signals in the next layer of the retina, the bipolar cells, and these signals are transmitted through the

various neurons in the retina, until eventually they are transmitted out of the eye by ganglion cell fibers. These ganglion cell fibers flow out of the back of the eye and become fibers in the optic nerve. Ganglion cells can be mapped into P-cells and M-cells. P-cells contain major information of images on 'what', whereas M-cells contain edge information of images. That is, information related to perceiving 'What' is transmitted to P-cells; and P-cells comprise 80% of total ganglion cells and minimize the loss during transmission. Whereas, information related to 'Where' is sent to M-cells; and M-cells comprise 20% of total ganglion cells (Duncan, 1984)

The biological retina is more than just a simple video camera. It not only converts optical information to electrical signals but performs considerable processing on the visual signal itself before transmitting it to higher levels. Various local adaptation mechanisms extend the retina's dynamic range by several orders of magnitude. In order to meet the transmission bottleneck at the optic nerve, the retina extracts only those features required at later stages of visual information processing (suyung, 2001).

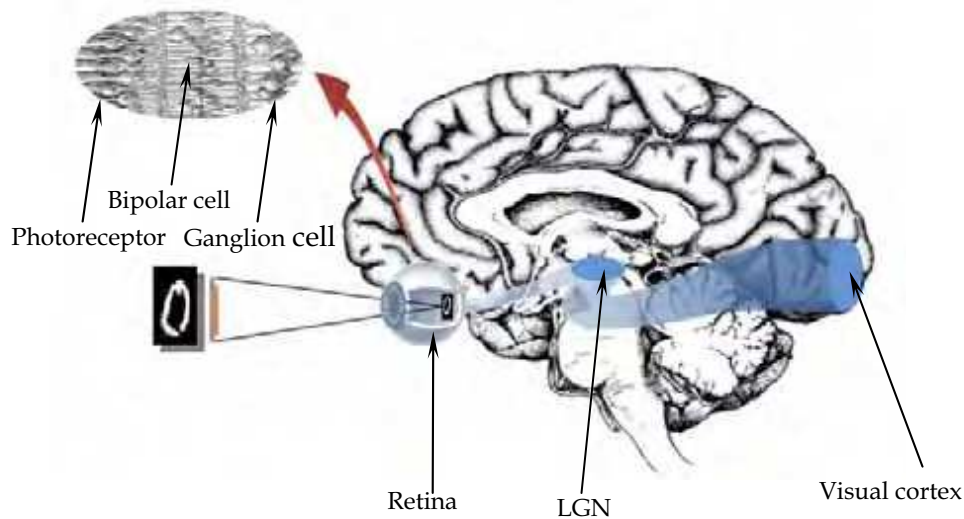


Figure 1. The processing steps of human vision system

Third, most of these optic nerve fibers reach the lateral geniculate nucleus (LGN), the first major way station on the way to the brain. The LGN is a bilateral nucleus, which means that there is an LGN on the left side of the brain, and also one on the right side. Finally, fibers transfer from the LGN to the primary visual receiving area, the striate cortex, or V1 in the occipital lobe. In conclusion, the main properties in human visual processing are as follows:

First, in retinal cells, the large difference between the number of receptors and the number of ganglion cells means that signals from many receptors converge onto each ganglion cell. Second, in visual cortex, this cell responds to the directions such as vertical, horizontal and orthogonal. Finally, the signal from ganglion cells coming from retina in fovea needs more space on the cortex than the signals from retina in periphery. The result is the cortical magnification factor (Bruce, 2002).

We propose the magnification method considering the properties of human visual processing in section 3.

3. Image magnification by the properties of human vision system

Based on the properties of human visual processing discussed in section 2, we now describe a magnification method for improving the performance of conventional image magnification methods.

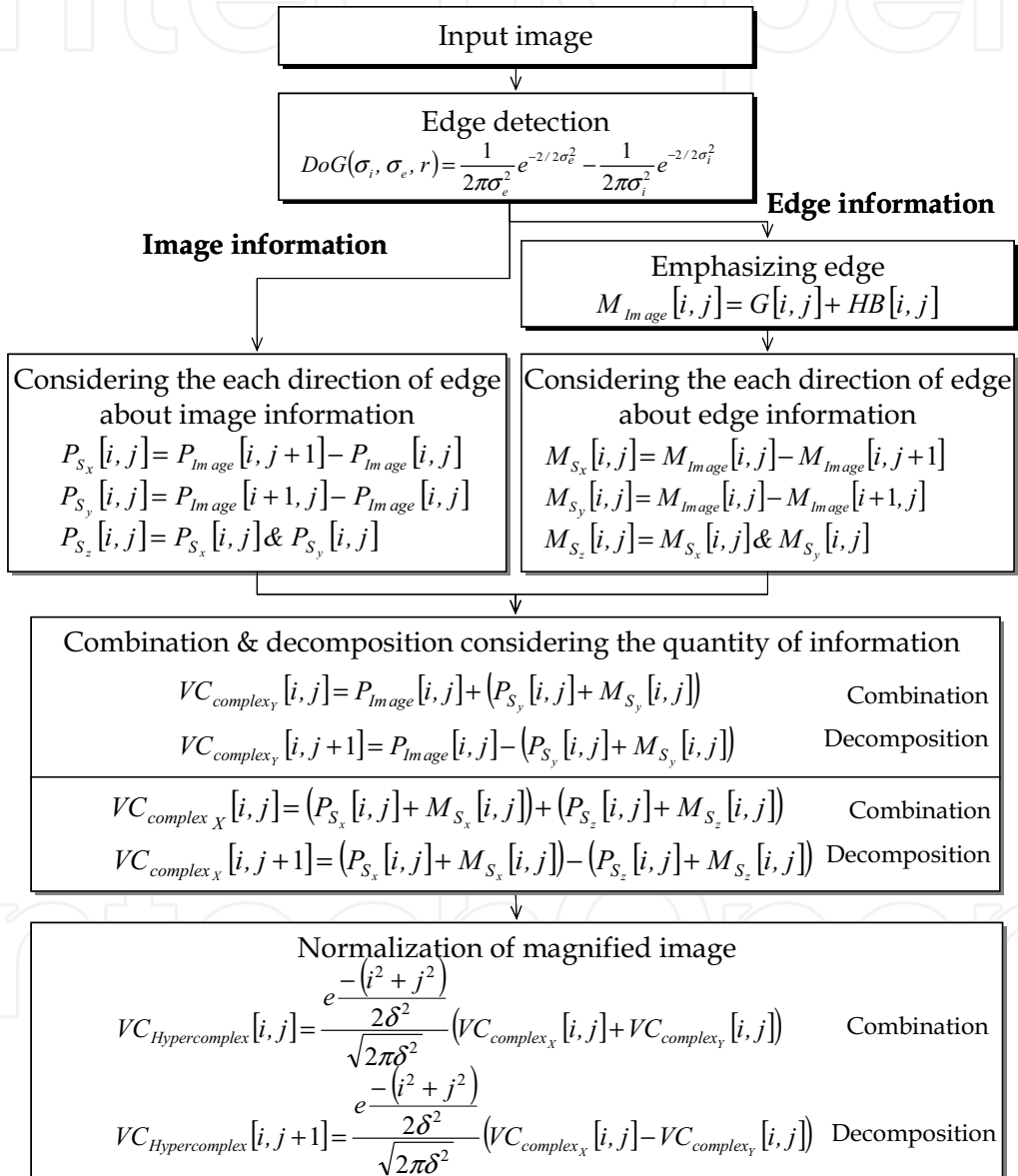


Figure 2. Proposed algorithm

Human vision system does not transfer image information from retina to visual cortex in the brain directly. By the properties of retinal cells, there is the reduction of information when vision information is transferred from receptors to ganglion cells. In addition, the reduced information from retina is transfer to the visual cortex with the magnified information. We proposed the magnification method with these properties. The proposed magnification uses edge information which is not used in interpolation based image processing. In image processing, the interpolated magnified image uses the average or offset of neighborhood pixels. It is not an ideal method since it only uses neighborhood pixels.

The edge information is important to distinguish the background and object. If a pixel were edge information, it wouldn't be able to distinguish the background and object using neighborhood pixels. It was insufficient to detect the edge information. In this paper, we calculated the edge information of a whole image. In order to solve the problem of magnification, the direction of the edge information will be considered. The schematic diagram of the method is shown as Fig. 2.

3.1 Edge Detection

First, we calculated the edge information from the input image. There are many methods in edge detection such as Laplacian operator, Sobel operator and Gaussian operator. In this paper, we calculated the edge information by using the DoG (Difference of two Gaussian) function, which is used in the human vision system. Wilson proposed the model that has been detected the edge information by the simulated results. It was simulated in the retina of the human vision system using the second derivative function $\nabla^2 G$ (LoG, Laplacian of a Gaussian). According to Marr and Hildreth, the DoG function has similar result to $\nabla^2 G$. And it is faster and more effective about the intensity change detection of the image than $\nabla^2 G$ (Dowling, 1987; suyung, 2001). In this paper, by setting the distance from the center as r , in equation (4), one obtains temporal change in the input image by the Gaussian filter.

$$G_e(\sigma_e, r) = \frac{1}{2\pi\sigma_e^2} e^{-r^2/2\sigma_e^2} \quad (4)$$

$$G_i(\sigma_i, r) = \frac{1}{2\pi\sigma_i^2} e^{-r^2/2\sigma_i^2} \quad (5)$$

$$DoG(\sigma_i, \sigma_e, r) = \frac{1}{2\pi\sigma_e^2} e^{-r^2/2\sigma_e^2} - \frac{1}{2\pi\sigma_i^2} e^{-r^2/2\sigma_i^2} \quad (6)$$

Consequently, by setting the excitatory synapsing standard deviation as σ_e , inhibitory synapsing standard deviation as σ_i , excitatory synapsing distribution as $G_e(\sigma_e, r)$, and inhibitory synapsing distribution as $G_i(\sigma_i, r)$, in equation (6), one obtains a symmetrical structure using the DoG function. It was optimal filter to the signal stimulated overlapping each other cells when the Gaussian function's standard deviation ratio is $\sigma_i / \sigma_e = 1.6$. The DoG function has similar result to the cell's reaction in the human vision.

However, it has less edge information than the other second derivative functions (Laplacian operator and Sobel operator) which are used mostly in image processing. In order to solve the problem, we propose an algorithm that emphasizes the image by using contrast regions. The Unsharp mask tool is used to emphasize an image in image processing. However, it causes a loss of the image and that adds the noise to the image and in result, it drastically reduces intensity gradient when the image is sharpened spatial edges, namely, emphasized contrast region. To solve the problem, we added the convoluted high-boost filter and edge information again.

$$M_{Image}[i, j] = G[i, j] + HB[i, j]$$

where,

$$HB = -\frac{\alpha}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & w/\alpha & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad (7)$$

$$w = 9\alpha - 1$$

HB is a high-boost filter. It sharpened the image and added to $G[i, j]$. By setting $w = 9\alpha - 1$, in equation (7), one obtains the enhanced edge information ($M_{Image}[i, j]$). The proposed method improves sensitivity to detect the edge of an object.

3.2 Magnification using Combination & Decomposition

In the field of computer vision, many researches have been conducted in relation with edge information to solve the problem of magnification. The edge information was composed of through high frequencies. Accordingly, it is important to restore the high frequency in magnification to solve the problem like blurring phenomenon. In image processing, a possible solution is edge detection that uses the second derivation function. But, it causes a loss of image by the error of edge information. It is the zero crossing in edge detection that detects edge gradients (Schultz & Stevenson, 1994; Gonzalez & Richard, 2001). We proposed the magnification algorithm that considered the direction of edge. To solve the problem like the error of edge information, we calculated each direction (horizontal, vertical and diagonal) to the input image and calculated the edge information. We used the difference operation which is the simplest and fastest operation in edge detection using gradient function. In equation (8), we calculated the horizontal and vertical direction by using the difference operation that calculated the increment of the input image ($i+1$). It is the difference in pixel brightness to the neighborhood pixel, namely, which calculated the gradient.

$$P_{S_x}[i, j] = P_{Image}[i+1, j] - P_{Image}[i, j] \quad (8)$$

$$P_{S_y}[i, j] = P_{Image}[i, j+1] - P_{Image}[i, j] \quad (9)$$

By setting the input image to P_{Image} , in equation (8), one obtains the vertical direction of input image P_{S_y} . In the same way, in equation (9), one obtains the horizontal direction of the input image P_{S_x} where i and j are the vertical and horizontal index of image.

The diagonal direction uses the vertical direction and horizontal direction. By setting the diagonal direction to P_{S_z} , in equation (10), one calculates the AND operation to the vertical direction and horizontal direction.

$$P_{S_z}[i, j] = P_{S_x}[i, j] \& P_{S_y}[i, j] \quad (10)$$

Information on the vertical, horizontal and diagonal direction of the input image was calculated through the use of equation (8), (9) and (10). In the same way, information on the vertical, horizontal and diagonal direction of the detected edge information was calculated by using equation (11).

$$\begin{aligned} M_{S_y}[i, j] &= M_{Image}[i, j] - M_{Image}[i + 1, j] \\ M_{S_x}[i, j] &= M_{Image}[i, j] - M_{Image}[i, j + 1] \\ M_{S_z}[i, j] &= M_{S_x}[i, j] \& M_{S_y}[i, j] \end{aligned} \quad (11)$$

In equation (11), M_{Image} is the detected edge information, M_{S_y} is the vertical direction in the detected edge information, M_{S_x} is the horizontal direction, and M_{S_z} is the diagonal direction.

Thus, we calculated 7 pieces of information collected from the input image. They were the detected edge information, vertical, horizontal, diagonal direction of input image and vertical, horizontal, diagonal direction of the detected edge information. They all have a position, direction and edge information. However, they have different quantities of information in regards to the edge. It holds different quantities of information for the vertical direction of the input image and detected edge information. The difference in the quantity of information in the vertical and horizontal direction is due to the edge. By equation (8), the detected edge information was an error on the left hand side of the ideal detecting edge information by the difference operation. In the same way, by equation (11), the detected edge information has an error on the right hand side of the ideal detecting edge information by the difference operation. To solve this problem, we calculated the ADD operation to the same direction of the detected edge information. And we processed the combination and decomposition considering the quantity of image information (pixel intensity) and edge information in each direction, the input image and 7 pieces of information. Therefore, most of the information contained is made up of the input image, the vertical direction of input image and the vertical direction of the detected edge information.

By setting, the larger quantity of image information and direction as $VC_{complex_y}$ and the smaller quantity of image information and direction as $VC_{complex_x}$, we can process the combination and decomposition in equation (12).

$$\begin{aligned} VC_{complex_y}[i, j] &= P_{Image}[i, j] + (P_{s_y}[i, j] + M_{s_y}[i, j]) \\ VC_{complex_y}[i, j+1] &= P_{Image}[i, j] - (P_{s_y}[i, j] + M_{s_y}[i, j]) \end{aligned} \quad (12)$$

By setting, the input image as P_{Image} , the vertical direction of the input image as P_{s_y} , and the vertical direction of the detected edge information as M_{s_y} , one obtains a large quantity of image information and direction. This is known as $VC_{complex_y}$. The $VC_{complex_y}$ is a combination of the input image and the vertical direction that is added to the vertical direction of the input image and the detected edge information. When the combination of the larger quantity of images is created, we process the ADD operation. In the same way, when there is a decomposition of the smaller quantity of images, we process the difference operation. Accordingly, we emphasized the edge information by using the ADD and difference operation for the combination and decomposition.

First, we calculated the ADD operation to the same direction of the input image and the calculated edge information. The $VC_{complex_y}$ was a combination of the larger quantity of images which was in the horizontal direction and this was added to the horizontal direction of the input image and the calculated edge information. When there is a combination of the larger quantity of images, we use the ADD operation.

$$\begin{aligned} VC_{complex_x}[i, j] &= (P_{s_x}[i, j] + M_{s_x}[i, j]) + (P_{s_y}[i, j] + M_{s_y}[i, j]) \\ VC_{complex_x}[i, j+1] &= (P_{s_x}[i, j] + M_{s_x}[i, j]) - (P_{s_y}[i, j] + M_{s_y}[i, j]) \end{aligned} \quad (13)$$

By setting, the horizontal direction of the input image as P_{s_x} , the diagonal direction of the input image as P_{s_y} , the horizontal direction of the detected edge information as M_{s_x} and the diagonal direction of the detected edge information as M_{s_y} , in equation (13), one obtains a smaller quantity of image information and its direction is $VC_{complex_x}$. The $VC_{complex_x}$ is a combination of the horizontal and diagonal direction that was added to the horizontal and diagonal direction of the input image and the detected edge information. In the same way as equation (12), when it is a decomposition of the smaller quantity of images, we process the difference operation. Likewise, we emphasized the edge information by using the ADD and difference operation for the combination and decomposition. We were able to obtain the magnified image by using the combination and decomposition to solve the problem of loss of high frequencies. But the magnified image has too much information on high frequencies in the $VC_{complex_y}$ and $VC_{complex_x}$. To reduce the risk of error of edge information in high frequencies, we processed the normalizing operation by using the Gaussian operator. The Gaussian operator is usually used in analyzing brain waves in visual cortex. And once a suitable mask has been calculated, and then the Gaussian smoothing can be performed using standard convolution methods.

$$\begin{aligned}
 VC_{hypercomplex}[i, j] &= \frac{e^{-\frac{(i^2 + j^2)}{2\delta^2}}}{\sqrt{2\pi\delta^2}} (VC_{complex}[i, j] + VC_{complex}[i, j]) \\
 VC_{hypercomplex}[i, j+1] &= \frac{e^{-\frac{(i^2 + j^2)}{2\delta^2}}}{\sqrt{2\pi\delta^2}} (VC_{complex}[i, j] - VC_{complex}[i, j])
 \end{aligned} \tag{14}$$

By setting, the average of input image as δ , the Gaussian operator as $\frac{e^{-\frac{(i^2 + j^2)}{2\delta^2}}}{\sqrt{2\pi\delta^2}}$, thus one can obtain the magnified image $VC_{complex}$.

In summary, first, we calculated edge information by using the DoG function and emphasized the contrast region by using the enhanced Unsharp mask. We calculated each direction of the input image and edge information to reduce the risk of error in the edge information. To evaluate the performance of the proposed algorithm, we compared it with the previous algorithm that was nearest neighborhood interpolation, bilinear interpolation and cubic convolution interpolation.

4. Experimental results

We used the Matlab 6.5 in a Pentium 2.4GHz, with 512MB memory, in a Windows XP environment and simulated the computational retina model based on the human visual information processing that is proposed in this paper. We used the SIPI Image Database and HIPR packages which is used regularly in other papers on image processing. SIPI is an organized research unit within the School of Engineering founded in 1971 that serves as a focus for broad fundamental research in signal and image processing techniques at USC. It has studied in all aspects of signal and image processing and serviced to available SIPI Image Database, SIPI technical reports and various image processing services. The HIPR (Hypermedia Image Processing Reference) serviced a new source of on-line assistance for users of image processing. The HIPR package contains a large number of images which can be used as a general purpose image library for image processing experiments. It was developed at the Department of Artificial Intelligence in the University of Edinburgh in order to provide a set of computer-based tutorial materials for use in taught courses on image processing and machine vision. In this paper, we proposed the magnification by using edge information to solve the loss of image problem like the blocking and blurring phenomenon when the image is enlarged in image processing. In performance, the human vision decision is the best. However, it is subjective decision in evaluating the algorithm. We calculate the PSNR and correlation to be decided objectively between the original image and the magnified image compared with other algorithms.

First, we calculated the processing time taken for the 256×256 sized of the Lena image to become enlarged to a 512×512 size. In Fig. 3, the nearest neighborhood interpolation is very fast in processing time (0.145s), but it loses parts of the image due to the blocking phenomenon. The bilinear interpolation is relatively fast in the processing time (0.307s), but it also loses parts of the image due to the blurring phenomenon. The cubic convolution interpolation does not have any loss of image by the blocking and blurring phenomenon,

but is too slow in the processing time (0.680) because it uses 16 neighborhood pixels. The proposed algorithm solved the problem of image loss and was faster than the cubic convolution interpolation in the processing time (0.436s).

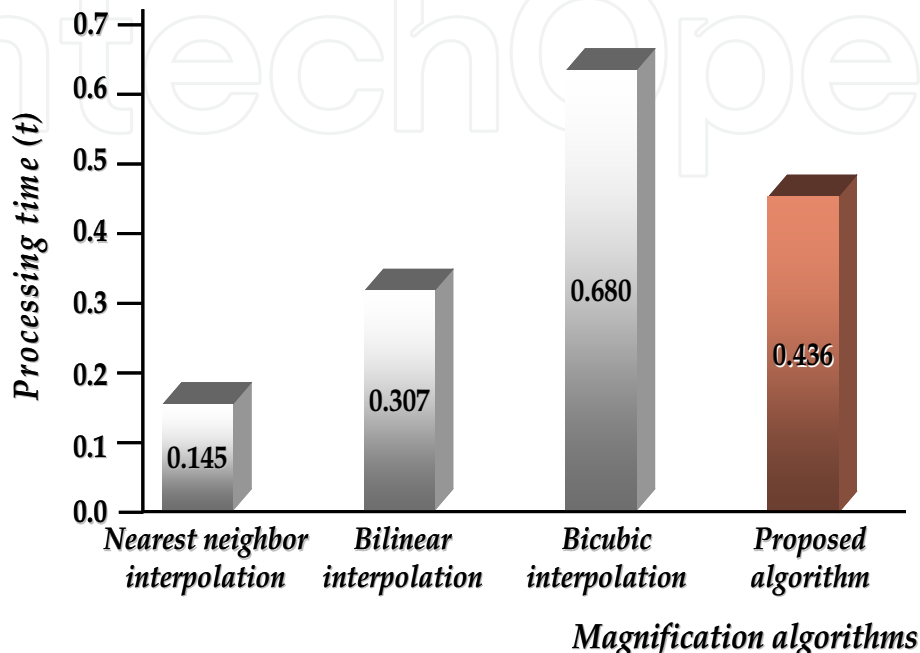


Figure 3. Comparison of the processing time of each algorithm

To evaluate the performance in human vision, Fig. 4, shows a reduction of 512×512 sized Lena image to a 256×256 sized by averaging 3×3 windows. This reduction is followed by an enlargement to the 512×512 sized image through the usage of each algorithm. We enlarged the central part of the image 8 times to evaluate vision performance. In Fig. 4, we can find the blocking phenomenon within vision in the nearest neighborhood interpolation (b). And we can also find the blurring phenomenon within vision in the bilinear interpolation(c). The proposed algorithm has a better resolution than the cubic convolution interpolation in Fig. 4(d, e).

We calculated the PSNR for objective decision. By setting the original image as X , and the magnified image as X^* , in equation (15), one obtains the PSNR.

$$PSNR = 20 \log_{10} \frac{255^2}{MSE} \quad (15)$$

$$MSE = \frac{1}{N} \frac{1}{M} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} (X(i, j) - X^*(i, j))^2$$

The MSE is a mean square error between the original image and the magnified image. Generally, the PSNR value is 20~40db, but the difference can not be found between the cubic convolution interpolation and the proposed algorithm in human vision. In table 1, there exist difference between two algorithms. The bilinear interpolation has a loss of image

due to the blurring phenomenon, but the PSNR value is 29.92. This is better than the cubic convolution interpolation which has a value of 29.86. This is due to the reduction taken place by the averaging method which is similar to the bilinear interpolation. We can conclude from the table 1 that the proposed algorithm is better than any other algorithm as the PSNR value is 31.35.

$$\begin{aligned} X &= X - Average(X) \\ X^* &= X^* - Average(X^*) \end{aligned} \tag{16}$$
$$Cross-correlation(X, X^*) = \frac{\sum_{i=0}^n X_i \sum_{i=0}^n X_i^*}{\sqrt{\sum_{i=0}^n X_i^2} \sqrt{\sum_{i=0}^n X_i^{*2}}}$$

To evaluate objectively in another performance, we calculated the cross-correlation in equation (16). In table 1, the bilinear interpolation is better than the cubic convolution interpolation in regards to the PSNR value. It also has similar results in cross-correlation. This is because we reduced it by using the averaging method and this method is similar to the bilinear interpolation. Thus we can conclude that the proposed algorithm is better than any other algorithm since the cross-correlation is 0.990109.

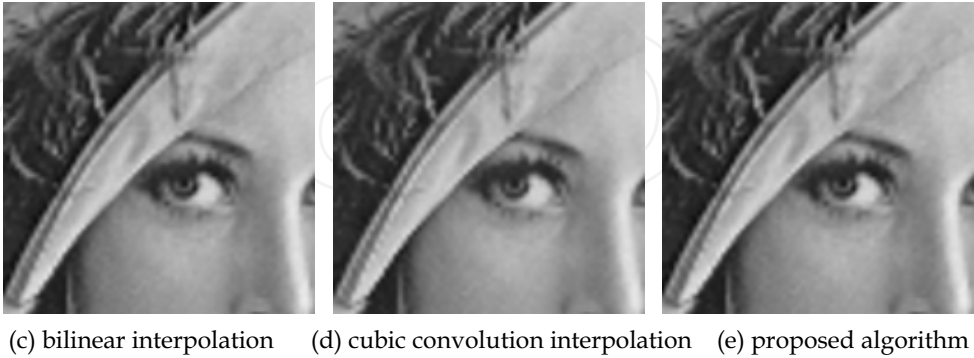
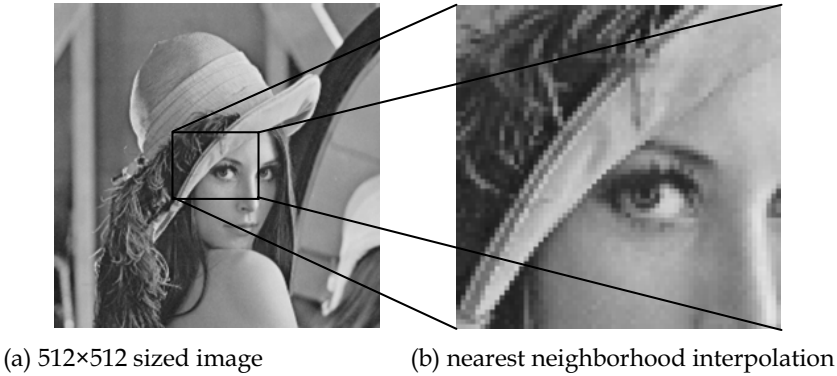


Figure 4. Comparison of human vision of each algorithm

Evaluation performance Magnification method	PSNR(db)	Cross-correlation
Nearest neighborhood interpolation	19.54	0.978983
Bilinear interpolation	29.92	0.985436
Cubic convolution interpolation	29.86	0.985248
Proposed algorithm	31.35	0.990109

Table 1. Comparison of Evaluation performance of each algorithm by averaging 3×3 windows

Performance Magnification method	PSNR(db)	Cross-correlation
Nearest neighbor interpolation	29.86	0.987359
Bilinear interpolation	30.72	0.989846
Cubic convolution interpolation	31.27	0.991336
Proposed algorithm	31.67	0.991363

Table 2. Comparison of Evaluation performance of each algorithm by the mean of a 3×3 window

Standard images Magnification method	Baboon	Peppers	Aerial	Airplane	Boat
Nearest neighbor interpolation	20.38	26.79	22.62	32.55	25.50
Bilinear interpolation	23.00	31.10.	25.46	33.44	25.50
Cubic convolution interpolation	23.64	31.93	26.64	33.72	29.39
Proposed algorithm	23.81	32.04	27.65	34.52	30.27

Table 3. Comparison of the PSNR of our method and general methods in several images

In Table 2, we reduced the image by the mean of 3×3 windows to evaluate objectively in another performance. And then, we enlarged to a 512×512 sized image by using each algorithm. We calculated the PSNR and cross-correlation again. The bilinear interpolation's PSNR value is 30.72, and the cubic convolution interpolation's PSNR value is 31.27. Thus, the cubic convolution interpolation is better than the bilinear interpolation. The proposed algorithm is better than any other algorithm in that the PSNR and cross-correlation can be obtained by using reduction through averaging and reduction by the mean. The proposed algorithm uses edge information to solve the problem of image loss. In result, it is faster and has higher resolution than cubic convolution interpolation. Thus, we tested other images (Baboon, Pepper, Aerial, Airplane, and Barbara) by the cross-correlation and PSNR in Table 3 and 4. Table 3 and 4 show that the proposed algorithm is better than any other methods in PNSR and Correlation on other images.

Standard images \ Magnification method	Baboon	Peppers	Aerial	Airplane	Boat
Nearest neighbor interpolation	0.834635	0.976500	0.885775	0.966545	0.857975
Bilinear interpolation	0.905645	0.991354	0.940814	0.973788	0.977980
Cubic convolution interpolation	0.918702	0.992803	0.954027	0.975561	0.982747
Proposed algorithm	0.921496	0.993167	0.963795	0.976768	0.986024

Table 4. Comparison of the correlation value of our method and general methods in several images

5. Conclusions

In image processing, the interpolated magnification method brings about the problem of image loss such as the blocking and blurring phenomenon when the image is enlarged. In this paper, we proposed the magnification method considering the properties of human visual processing to solve such problems. As a result, our method is faster than any other algorithm that is capable of removing the blocking and blurring phenomenon when the image is enlarged. The cubic convolution interpolation in image processing can obtain a high-resolution image when the image is enlarged. But the processing is too slow as it uses the average of 16 neighbor pixels. The proposed algorithm is better than the cubic convolution interpolation in the processing time and performance. In the future, to reduce the error ratio, we will enhance the normalization filter which has reduced the blurring phenomenon because the Gaussian filter is a low pass one.

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Vision Systems: Applications

Edited by Goro Obinata and Ashish Dutta

ISBN 978-3-902613-01-1

Hard cover, 608 pages

Publisher I-Tech Education and Publishing

Published online 01, June, 2007

Published in print edition June, 2007

Computer Vision is the most important key in developing autonomous navigation systems for interaction with the environment. It also leads us to marvel at the functioning of our own vision system. In this book we have collected the latest applications of vision research from around the world. It contains both the conventional research areas like mobile robot navigation and map building, and more recent applications such as, micro vision, etc. The first seven chapters contain the newer applications of vision like micro vision, grasping using vision, behavior based perception, inspection of railways and humanitarian demining. The later chapters deal with applications of vision in mobile robot navigation, camera calibration, object detection in vision search, map building, etc.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Sung-Kwan Je, Kwang-Baek Kim, Jae-Hyun Cho and Doo-Heon Song (2007). Image Magnification Based on the Human Visual Processing, Vision Systems: Applications, Goro Obinata and Ashish Dutta (Ed.), ISBN: 978-3-902613-01-1, InTech, Available from:
http://www.intechopen.com/books/vision_systems_applications/image_magnification_based_on_the_human_visual_processing

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