Paper

Local Contrast Enhancement by Optimizing Image Separation Using Genetic Algorithm

Member Fumihiko Saitoh (Gifu University)

This paper proposes a method to obtain a good contrast image by optimizing the number of local areas and by changing the positions of the boundaries for local contrast enhancement according to the conditions of an objective gray-scaled image. The genetic algorithm is applied to determine the optimal image separation. A chromosome is represented by a pair of arrays that show the positions of the boundaries to separate an image. The fitness of an individual is evaluated by the sharpness of the image that is measured by the delta-histograms of the enhanced image and the blurred image. The experimental results show that the natural enhanced images with few noises were generated by the proposed method in comparison with the conventional methods.

Keywords: Contrast enhancement, Image separation, Genetic algorithm, Liner interpolation

1. Introduction

Image contrast enhancement is an important process to improve image quality and to perform reliable image recognition. The typical conventional methods for image contrast enhancement are the liner gray-level transform that expands the dynamic range of gray-levels linearly and the histogram equalization that converts gray-levels so as to uniform the distribution of a histogram[1]~[3]. However, these methods do not necessarily work effectively when the contrast of a partial area in an image is not good because the whole image is processed in the block. To solve this problem, the method for local contrast enhancement has been proposed that separates an objective image to plural local areas and coverts gray-levels according to the distribution of gray-levels in each local area[4]. However, the conventional method for local contrast enhancement always separates an image equally. In other words, the separated local areas have the same form, the same size and the fixed locations regardless of the conditions of an objective image. Also, the optimal number of separated local areas must be decided empirically.

This paper proposes a method to obtain a good contrast image by optimizing the number of separated local areas and by changing the positions of the boundaries for image separation dynamically according to the conditions of an objective gray-scaled image. The genetic algorithm[5],[6] is applied to determine the optimal image separation in the proposed method.

2. Local contrast enhancement

This chapter describes the conventional methods for local contrast enhancement. Firstly, the method has been proposed that determines the gray-level of a pixel by means of the liner transform or by means of the histogram equalization using the distribution of gray-levels of all pixels in the local area that is set around the pixel[7]. This method requires enormous computational cost because the distribution of gray-levels must be measured repeatedly for all pixels in an objective image.

Thereupon, the improved method has been proposed that determines the gray-level of a pixel according to the relation

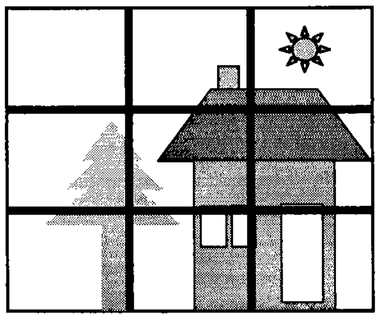


Fig.1 Local contrast enhancement by separating image equally

between input gray-levels and output gray-levels that is obtained from the distribution of gray-levels of all pixels in a separated local area as shown in Fig.1[4]. In this method, the image is separated equally and the liner interpolated gray-level is given to each pixel between the four gray-levels that are converted by the relations between input gray-levels and output gray-levels in the neighboring local areas. The computational cost can be reduced drastically in this method because the distribution of gray-levels is measured only in the separated local areas. However, many noises may occur or an unnatural enhanced result may be obtained in a local area with even gray-levels such as the upper-left background area shown in Fig.1 because the relation between input gray-levels and output gray-levels is set so as to enhance the contrast maximumly in each local area. Furthermore, it is supposed that this method is not so general-purpose because the optimal number of local areas must be determined empirically.

3. Optimal image separation by genetic algorithm

3.1 Fundamental concept In the conventional methods, an objective image is always separated equally and the optimal number of separated local areas must be determined empirically. In other words, the conditions for image separation are always fixed. On the other hand, the number of local areas and the positions of the boundaries to separate an

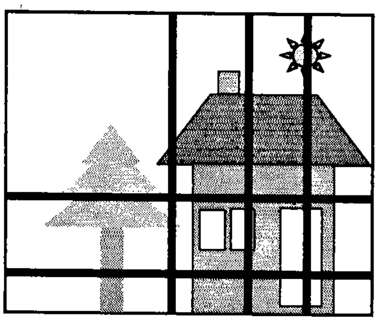


Fig.2 Local contrast enhancement by separating image unequally

image are variable in the proposed method as shown in Fig.2. Namely, the conditions for image separation are determined dynamically according to an objective gray-scaled image so as to obtain a good contrast image. However, there are huge combinations about the number of local areas and the positions of the boundaries for image separation. Thereupon, the optimal number of local areas and the optimal positions of the boundaries for separation are determined using the genetic algorithm.

The genetic algorithm is known as a method to solve an engineering problem efficiently by referring the evolutionary process of creatures. The following sections explain the concrete methods to determine the appropriate conditions to separate image for local contrast enhancement using the genetic algorithm.

3.2 Representation of chromosome This section describes the method to represent an individual chromosome. An individual chromosome has a pair of arrayed bits. One arrayed bits represents the positions of boundaries to separate an image vertically, another arrayed bits represents the positions of boundaries to separate the image horizontally as shown in Fig.3. The former will be called the array for vertical separation and the latter will be called the array for horizontal separation. The length of the array for vertical separation M is the same as the number of pixels to the horizontal direction in the image and the length of the array for horizontal separation N is the same as the number of pixels to the vertical direction

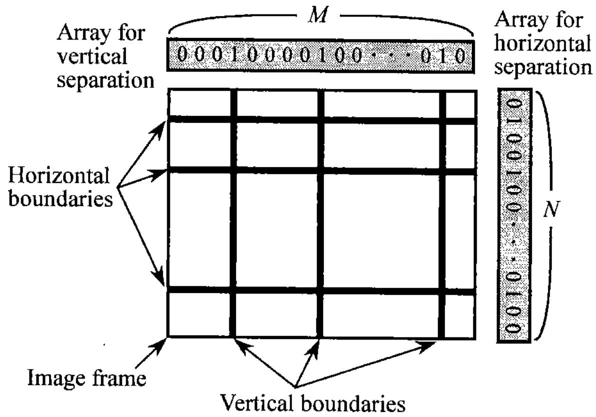


Fig.3 Representation of a chromosome

in the image as shown in Fig.3. Only elements including bit 1 in each array show the positions of boundaries to separate the image.

Combinations of random bits are given to the arrays in all individual chromosomes at the initialization process in the genetic algorithm. However, the ratio of the number of bit 1 to the number of bit 0 in the arrays is set to 1 to 32 in an initialized chromosome. It is because that the preliminary experimental result showed that the most natural enhanced images were obtained when the ratio of the number of bit 1 to the number of bit 0 was set to 1 to 32 in the conditions of 1 to 8, 1 to 16, 1 to 32 and 1 to 64. The appropriate number of local areas is supposed to be not so many for local contrast enhancement generally[9].

3.3 Evaluation of fitness Fig.4 shows the process to evaluate the fitness of an individual. An objective image is separated to local areas according to the positions of bit 1 set in the chromosome of an individual k. Next, the look-up-table that means the relation between input gray-levels and output gray-levels is obtained in order to transform gray-levels linearly in each local area. And, the gray-levels of all pixels in the image are converted through the liner interpolation between the four gray-levels that are transformed by the look-up-tables obtained in four surrounding local areas. The

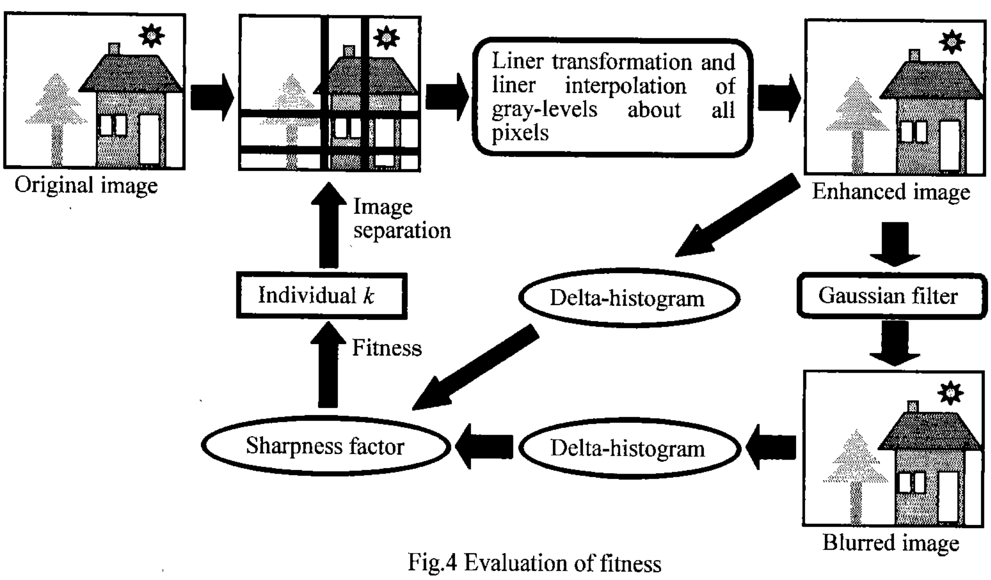


Fig.4 Evaluation of fitness

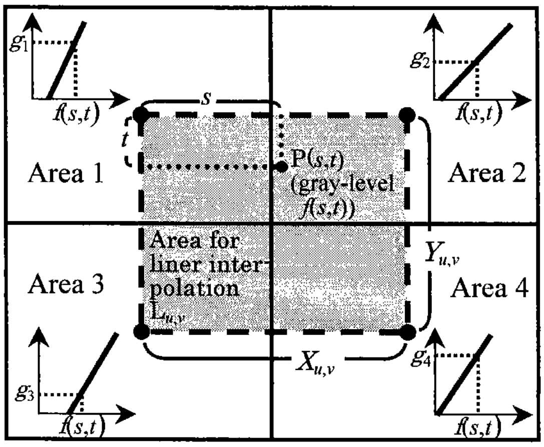


Fig.5 Determination of a pixel's value by liner interpolation between four gray-levels transformed by look-up-tables for surrounding central pixels

resultant image is generated through the above processes.

When the resultant image is judged to have a good contrast, the individual k is given a higher fitness. The following sections describe the concrete methods to evaluate the fitness of an individual.

3.3.1 Setting of look-up-tables Firstly, the objective image is separated to local areas according to the array for vertical separation and the array for horizontal separation in the chromosome of an individual k. Next, the look-up-table is set in each local area to transform the gray-level of a pixel linearly according to the maximum gray-level I_{mx} and the minimum gray-level I_{mn} in the local area. Namely, the look-up-table represents the liner relation between input gray-levels and output gray-levels transformed by the next expression.

$$g(x,y) = \frac{255\left(f(x,y) - I_{mn}\right)}{I_{mx} - I_{mn}} \quad (1)$$

$f(x,y)$ means an input gray-level and $g(x,y)$ means an output gray-level of a pixel.

3.3.2 Liner interpolation of gray-levels The look-up-table is set in each local area by the above-mentioned processes. By the way, an unnatural enhanced image may be generated because the discontinuations may occur just on the boundaries of local areas in the case of the gray-levels of pixels in a local area are transformed using only the look-up-table set in the local area. To solve this problem, the gray-levels of all pixels in the image are determined through the liner interpolation between the four gray-levels that are transformed by the four types of look-up-tables set in the neighboring local areas[8),(9)].

As shown in Fig.5, the look-up-table set in a local area is used to transform the gray-level of the pixel that is located on the center of the local area. And, the gray-level of a pixel that is not located on the center of the local area is determined through the liner interpolation between the four gray-levels that are transformed by the look-up-tables set for the central pixels of the local areas that surround the pixel. Here, a rectangular area that is closed by the four central pixels in local areas will be called the area for liner interpolation as shown in Fig.5. The size of an area for liner interpolation is determined according to the sizes of the four local areas that surround the area for liner interpolation. The size of an area for liner interpolation $L_{u,v}$ is supposed to be $X_{u,v} \times Y_{u,v}$ pixels and the gray-level of a pixel P(s,t) $(0 \leqq s < X_{u,v}-1,\ 0 \leqq t < Y_{u,v}-1)$ in the area is supposed to be $f(s,t)$. As shown in Fig.5, the gray-level $f(s,t)$ of the pixel P(s,t) is supposed to be transformed to g_1, g_2, g_3 and g_4 by the look-up-tables that are set for the central pixels of the four local areas surrounding the pixel P and located on the upper-left, the upper-right, the lower-left and the lower-right from the pixel P. In this case, the new gray-level is determined by the liner interpolation between the gray-levels g_1, g_2, g_3 and g_4 that is based on the relative locations between the pixel P and the four surrounding central pixels. Namely, the new gray-level $g_n(s,t)$ of the pixel P is calculated by the next expression.

$$g_n(x,y) = \frac{g_1 \cdot (X_{u,v}-s)(Y_{u,v}-t) + g_2 \cdot s \cdot (Y_{u,v}-t) + g_3 \cdot (X_{u,v}-s) \cdot t + g_4 \cdot s \cdot t}{X_{u,v} \cdot Y_{u,v}} \quad (2)$$

The gray-levels of all pixels in the image are determined by the above-mentioned method that converts the gray-level of a pixel through the liner interpolation using the four look-up-tables that are set for the surrounding central pixels.

The image is supposed to be expanded to the outside in order to determine the gray-levels of pixels that locate in the periphery area of the image through the liner interpolation. The sizes of the expanded areas are same as the sizes of the circumferential local areas in the image. The look-up-tables for the central pixels of the circumferential local areas are copied for the central pixels of the expanded areas. And, the gray-levels of all pixels in the periphery area of the image are set through the liner interpolation.

3.3.3 Evaluation of image using delta-histogram Next, the fitness of the individual k is evaluated according to the quality of the resultant image that is generated by the above-mentioned methods. Namely, the individual k is given a higher fitness as the image has better contrast.

It is difficult to define the objective visual contrast of an image. However, we feel that the image has good visual contrast when the image has a wide dynamic range of gray-levels and sharp contours[(10)]. The dynamic range that means the difference between the maximum gray-level and the minimum gray-level in the image can be expanded by the liner transform of gray-levels. On the other hand, *MTF* (*Modulation Transfer Function*) is generally used to evaluate the objective sharpness of the image[(11),(12)]. However, the special image pattern must be included in the image in order to measure *MTF*. It is therefore difficult to evaluate *MTF* in the proposed method because the objective images cannot include the special image pattern to measure *MTF* but natural scenes.

On the other hand, the method that uses the delta-histogram was developed to evaluate the sharpness of a natural scene image[(13)]. The factor to evaluate the sharpness of an image using the delta-histogram is reported to have the good correlation with *MTF*.

Thereupon, the proposed method uses the delta-histogram to evaluate the contrast of the generated image. The delta-histogram is represented by the distribution of the averaged differences of gray-levels of neighboring pixels. The differences of gray-levels are measured between an objective pixel and its neighboring eight pixels as shown in Fig.6 and the averaged value of eight differences is calculated. The delta-histogram is composed by the distribution of the averaged differences of gray-levels about all pixels in the image. To evaluate the sharpness of a natural scene image, the

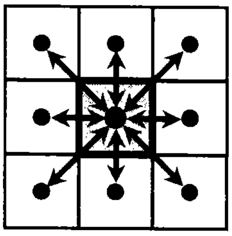


Fig.6 Differences of gray-levels between neighboring pixels

absolute summarized difference is calculated between the delta-histogram $D_o(n)$ (n=0,1,..,255) that is obtained from the objective image and the delta-histogram $D_b(n)$ (n=0,1,..,255) that is obtained from the blurred image. Namely, *SF(Sharpness Factor)* is calculated as the degree to evaluate the sharpness by the next expression[13].

$$SF = \sum_{n=0}^{255} \left| D_o(n) - D_b(n) \right| \tag{3}$$

SF means the diagonal area shown in Fig.7 that enclosed by both the delta-histograms.

SF will show a higher value in case that the objective image has good contrast because the image will be influenced greatly by the blurring process. On the other hand, *SF* will show a lower value in case that the objective image does not have good contrast because the image will not be changed remarkably by the blurring process. In the proposed method, the ratio of the value of *SF* about the enhanced image to the value of *SF* about the original input image is given to an individual as the fitness. Namely, the fitness $F_t(k)$ of an individual k is represented by the next expression.

$$F_t(k) = SF_E(k)/SF_O \tag{4}$$

Here, $SF_E(k)$ means the value of *SF* that is calculated by the expression(3) about the resultant image that is generated through the image separation according to the chromosome of the individual k and through the liner interpolation of gray-levels about all pixels. SF_O means the value of *SF* about the original input image that is not enhanced.

The Gaussian filter is applied in order to blur an image that has the similar characteristic to the visual defocus[14]. The gray-level $f(x,y)$ of a pixel P(x,y) is converted to $h(x,y)$ by the Gaussian filter represented by the next expression.

$$h(x,y) = \frac{\sum_j \sum_i f(x+j, y+i) \cdot G(j,i)}{\sum_j \sum_i G(j,i)} \tag{5}$$

$$G(j,i) = \frac{1}{2\pi\sigma^2} e^{-\frac{j^2+i^2}{2\sigma^2}} \tag{6}$$

The proposed method applies the Gaussian filter with 5×5 pixels size that is used for general defocusing process of an image.

3.4 Evolutionary rules This section describes the evolutionary rules in the genetic algorithm. The number of individuals in the population is set to a constant G. The only individuals to the number of $G \cdot S/100$ are survived to the next generation with a survived rate S%. In this case, the fitness of all individuals are calculated and only a part of individuals with the higher S% fitness are selected. On the other hand, the individuals with the lower 100-S% fitness are extinguished.

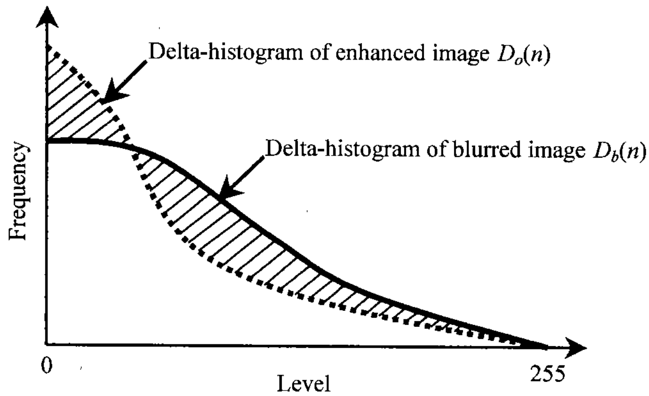


Fig.7 Delta-histograms and sharpness factor

Next, a pair of parent individuals is selected randomly in the survived individuals, and a child individual is generated by crossover. The number of children that are generated by crossover is the same as the number of extinguished individuals. Therefore, the total number of individuals in the population is kept a constant G during all generations.

3.5 Crossover and mutation A parent k_1 and a parent k_2 are selected randomly in the group of individuals that are survived to the next generation. And, the arrays for verticalseparation are crossovered between the chromosomes of the parent k_1 and the parent k_2. The arrays for horizontal separation are also crossovered similarly. The total number of bit 1 in the arrays can be changed after the crossover in the proposed method. Therefore, the general two-point crossover is applied.

An individual is selected randomly with a mutation rate M_u% in the population. And, a bit that is extracted randomly in the arrays of the individual is inversed.

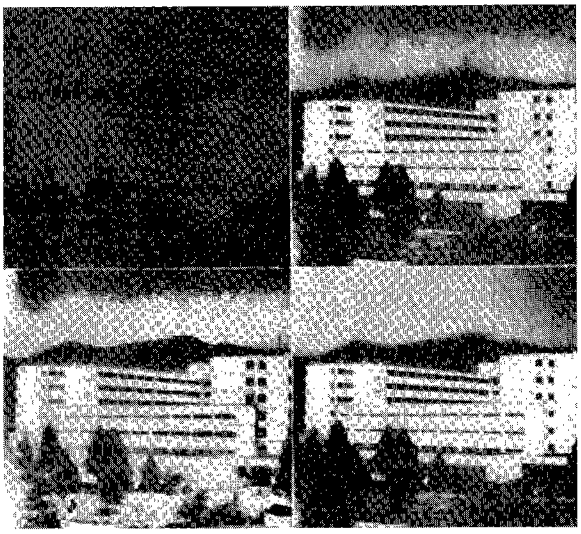
3.6 Conditions to complete algorithm The genetic algorithm is applied according to the above-mentioned rules and operations. Arrays of random bits are assigned to the chromosome of each individual in the first generation. When the maximum fitness in all individuals has been kept a constant during ten generations, the chromosome of the individual with the maximum fitness expresses the final solution obtained by the genetic algorithm. Namely, the image is separated by the boundaries corresponded to bit-1 in the chromosome for local contrast enhancement.

4. Experiments

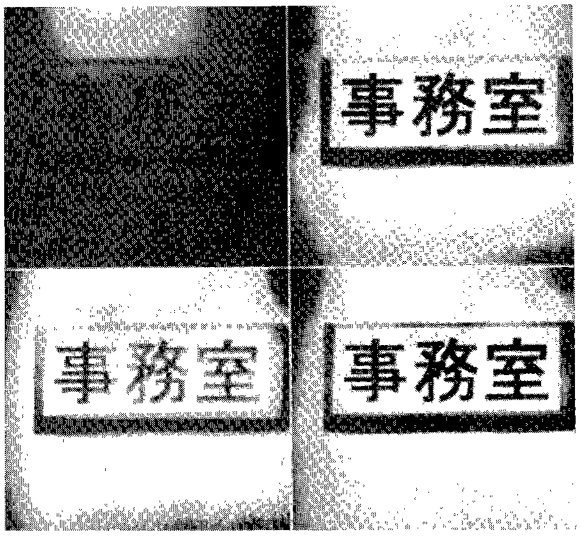
This chapter describes the experimental results to evaluate the proposed method.

4.1 Experimental conditions The size of the experimental gray-scaled images was 256×240 pixels and the gray-level of a pixel was digitized to 8 bits. The number of individuals in the population was set to G=200, the survived rate was set to S=50% and the mutation rate was set to M_u=0.1% experimentally.

The conventional methods for local contrast enhancement that separate an image equally were also experimented to compare with the proposed method. In the conventional methods, the number of local areas was set to the optimal fixed 4×4 in the 2×2, 4×4 and 8×8 that were experimented. And, both the liner gray-level transformation and the histogram equalization were experimented as the conventional

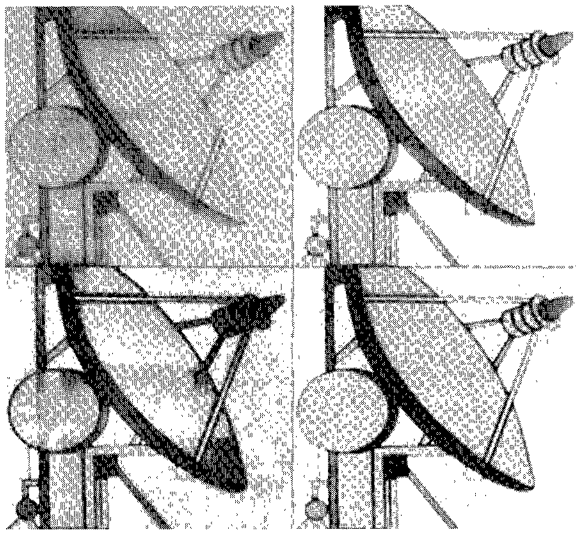


(a)campus



(b)plate

(c)tree



(d)antenna

Fig.8 Contrast enhanced images (upper-left: original image, upper-right: by the method to separate image equally and transform gray-levels linearly, lower-left: by the method to separate image equally and transform gray-levels through the histogram equalization, lower-right: by the proposed method)

methods to generate look-up-tables in the separated local areas.

The experimental gray-scaled images were (a)campus, (b)plate, (c)tree and (d)antenna. These images were captured by TV camera with the narrow iris because the experimental images must have low contrast to evaluate the proposed method. (a)campus and (c)tree were natural scene images including the complex backgrounds and (b)plate and (d)antenna were composed by the character string or the printed figure and the simple backgrounds influenced by the shading.

4.2 Comparison of enhanced images Fig.8 shows the enhanced images by the conventional methods and the proposed method. The upper-left shows the original gray-scaled image, the upper-right shows the result by the method that separates an image equally and transforms gray-levels linearly, the lower-left shows the result by the method that separates an image equally and transforms gray-levels through the histogram equalization and the lower-right shows the result by the proposed method in each image shown in Fig.8. The numbers of local areas were 5×6 about (a)campus, 7×4 about (b)plate, 5×7 about (c)tree and 3×4 about (d)antenna finally in the results by the proposed method.

In the results about (a)campus, many conspicuous noises occurred in the background area with even gray-level although the enhanced image had the natural contrast in the case of using the conventional method that separates an image equally and transforms gray-levels linearly. Especially, there were many noises in the sky area that occupies the upper part of the image. Next, the unnatural and noisy enhanced image was obtained visually by the conventional method that separates an image equally and transforms gray-levels through the histogram equalization because the different pixels that had a

Table1 Fitness by the enhancement methods

Method / Image	Method to separate image equally and transform gray-levels linearly	Method to separate image equally and transform gray-levels through the histogram equalization	Proposed method
(a)campus	1.17	1.19	1.24
(b)plate	1.97	1.64	2.48
(c)tree	1.03	0.98	1.08
(d)antenna	1.08	0.98	1.11

Table3 Experimental result of subjective contrast evaluation

Image	Method	Method to separate image equally and transform gray-levels linearly				Method to separate image equally and transform gray-levels through the histogram equalization				Proposed method			
	Rank	1	2	3	Averaged rank	1	2	3	Averaged rank	1	2	3	Averaged rank
(a)campus	Contrast	1	10	0	1.9	0	0	11	3.0	10	1	0	1.1
	Noiselessness	0	11	0	2.0	0	0	11	3.0	11	0	0	1.0
	Natural impression	2	9	0	1.8	0	0	11	3.0	9	2	0	1.2
	Total quality	0	11	0	2.0	0	0	11	3.0	11	0	0	1.0
(b)plate	Contrast	1	10	0	1.9	0	0	11	3.0	10	1	0	1.1
	Noiselessness	0	8	3	2.3	0	3	8	2.7	11	0	0	1.0
	Natural impression	1	10	0	1.9	0	0	11	3.0	10	1	0	1.1
	Total quality	0	11	0	2.0	0	0	11	3.0	11	0	0	1.0
(c)tree	Contrast	0	8	3	2.3	0	3	8	2.7	11	0	0	1.0
	Noiselessness	3	8	0	1.7	0	0	11	3.0	8	3	0	1.3
	Natural impression	3	8	0	1.7	0	0	11	3.0	8	3	0	1.3
	Total quality	1	10	0	1.9	0	0	11	3.0	10	1	0	1.1
(d)antenna	Contrast	0	11	0	1.0	0	0	11	3.0	11	0	0	1.0
	Noiselessness	3	8	0	1.7	0	0	11	3.0	8	3	0	1.3
	Natural impression	2	9	0	1.8	0	0	11	3.0	9	2	0	1.2
	Total quality	2	9	0	1.8	0	0	11	3.0	9	2	0	1.2

Table2 Conditions for evaluating subjective contrast

Item	Conditions
The number of subjects	11
Visual distance	3H (H: Height of display)
Illuminance in experimental room	110lx
The maximum luminance in display monitor	128cd/m^2
Display monitor	14inch color monitor (SONY: PVM-1442Q)

same gray-level before contrast enhancement might have different gray-levels through the process of the histogram equalization. On the other hand, the natural enhanced image was obtained by the proposed method as well as by the conventional method that separates an image equally and transforms gray-levels linearly. Furthermore, it is found that the image contrast was fine in the details of the building part and the garden part especially in the result by the proposed method. Moreover, there were considerably fewer noises in the background sky area in comparison with the results by the conventional methods.

In the results about (b)plate, the natural enhanced image that included the good contrast character string was obtained by the proposed method as well as by the method that separates an image equally and transforms gray-levels linearly. However, there were fewer noises in the background area in the result by the proposed method in comparison with the method that separates image equally and transforms gray-levels linearly. On the other hand, the inferior image with many noises and the lower contrast character string was obtained by the method that separates an image equally and transforms gray-levels through the histogram equalization.

In the results about (c)tree, the visual contrast of the enhanced image by the method that separates an image equally and transforms gray-levels linearly was not so good in comparison with the result of the proposed method. On the other hand, the enhanced image by the method that separates an image equally and transforms gray-levels through the histogram equalization had unnatural and too strong contrast in comparison with the result of the proposed method.

In the results about (d)antenna, the natural enhanced image without background noises was obtained by the proposed method. However the natural image was also obtained by the method that separates an image equally and transforms gray-levels linearly, the visual contrast of the resultant image was lower than the result of the proposed method. The inferior image with many noises was obtained by the method that separates an image equally and transforms gray-levels through the histogram equalization.

By the unequal and appropriate image separation in the proposed method, the natural results with few noises were obtained in the background local areas with even gray-levels in comparison with the conventional methods by the equal image separation.

Table 1 presents the values of the fitness about the enhanced images by three kinds of method. The final maximum fitness are shown in the case of the proposed method. It is found that the proposed method recorded the maximum fitness values about all images in comparison with the conventional methods.

4.3 Evaluation of subjective image quality The subjective quality of the resultant images enhanced by the above three kinds of methods was evaluated. The number of experimental subjects was eleven because the evaluation of visual image quality is experimented by about ten subjects

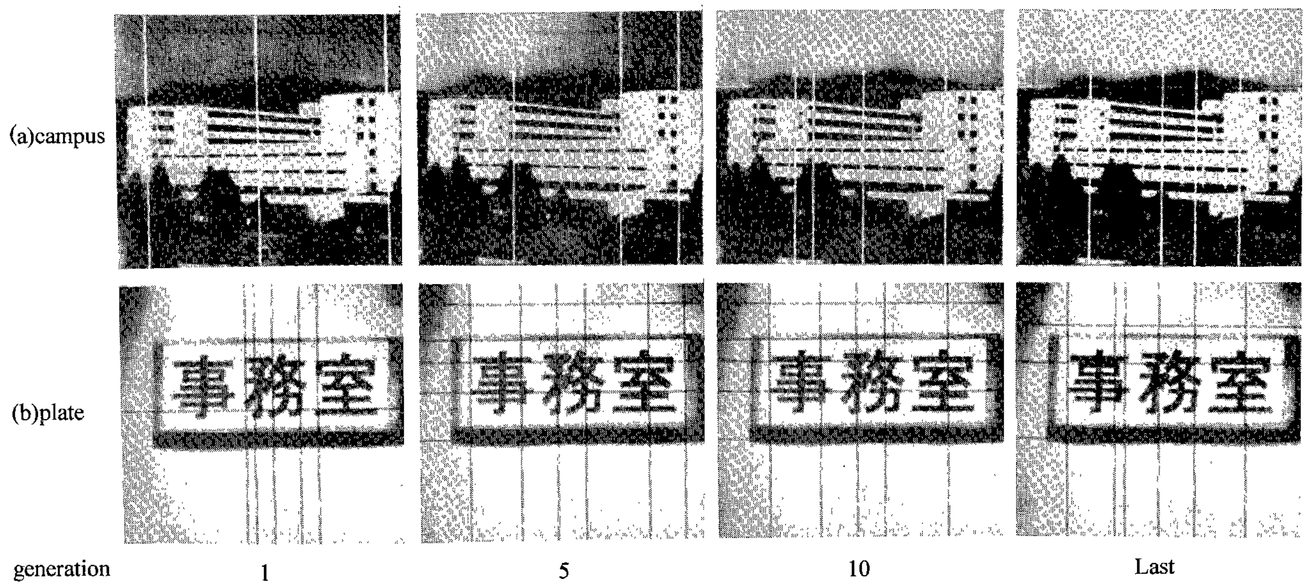


Fig.9 Changes of enhanced images in evolutionary process

generally[15],[16]. Table2 shows the experimental conditions. As shown in Fig.8, the original gray-scaled image, the result by the method that separates an image equally and transforms gray-levels linearly, the result by the method that separates an image equally and transforms gray-levels through the histogram equalization and the result by the proposed method are arranged and displayed on the display monitor at the same time. Each subject ranked the enhanced images by the three kinds of methods about the visual contrast, the noiselessness, the natural impression and the total image quality.

Table 3 shows the number of subjects who ranked each enhanced image and the averaged rank of the method about each evaluated item. The proposed method acquired the best rank about all evaluated items that were the visual contrast, the noiselessness, the natural impression and the total image quality. Most of the subjects also gave the first rank to the proposed method about all evaluated items. The method that separates an image equally and transforms gray-levels linearly recorded the second rank about all evaluated items. The method that separates an image equally and transforms gray-levels through the histogram equalization recorded the worst rank about all evaluated items. There was hardly the difference in the evaluated results among individual subjects. Most of the subjects were impressed that the enhanced images by the proposed method had the natural good contrast and the smooth gradation with few noises.

4.4 Evolutionary process Fig.9 shows the processes to optimize the separations of the images and the changes of the enhanced images in the evolutionary process of the genetic algorithm about (a)campus and (b)plate. The white and black straight lines in the images mean the positions of boundaries to separate the images that are represented by the individual chromosomes with the maximum fitness in the population. As the generation progressed in the genetic algorithm, the number of boundaries and their positions were changed dynamically and the contrast of the resultant image was enhanced gradually about each experimental image. The similar results were obtained about (c)tree and (d)antenna.

Fig.10 shows the relations between the progress of the generation and the maximum fitness in the population about (a)campus and (b)plate. The maximum fitness increased gradually and converged to the constants through the evolutionary process of about 30 generations. The similar evolutionary processes were also obtained about (c)tree and (d)antenna. Incidentally, the processing time for evolution was about 30 seconds for each experimental image by using PentiumIII-600MHz processor, Turbo-Linux and C language.

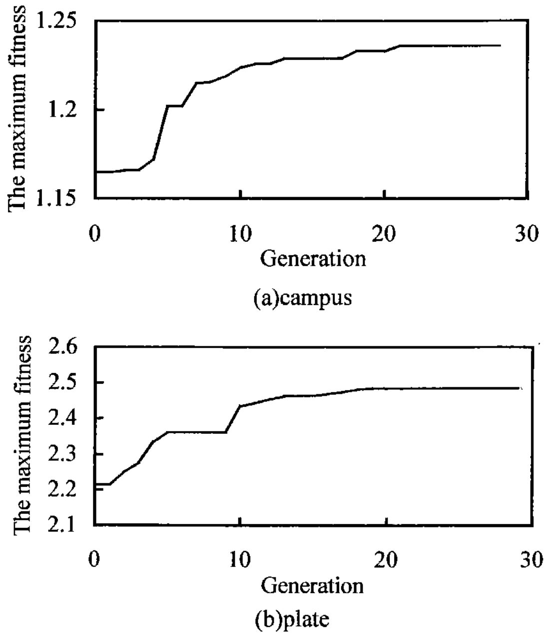


Fig.10 Relations between generation and the maximum fitness

5. Conclusions

A method for local contrast enhancement has been proposed by optimizing the status of image separation using the genetic algorithm. A chromosome is represented by a pair of arrays that show the positions of the boundaries to separate an image horizontally and vertically. The fitness of an individual is evaluated by the sharpness of the image that is obtained by the difference between the delta-histogram of the enhanced image and the delta-histogram of the blurred image. The experimental results show that the natural enhanced images with few noises in the background area were obtained by the proposed method in comparison with the conventional methods. It will be a future subject to reduce the processing time by improving the genetic operations and by developing the hardware to calculate the delta-histogram because the proposed method needs the computational cost.

(Manuscript received January 24, 2001, revised July 18,2001)

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Fumihiko Saitoh (Member) He received the B.E. degree from Keio University, Japan in1981 and the Dr. Information Sciences from Tohoku University in 1998. He joined IBM in 1981 and Hitachi Ltd. in 1995. From 1998 he was an Associate Professor in the Department of Software and Information Sciences, Iwate Prefectural University. He is currently an Associate Professor in the Department of Information Sciences, Gifu University, Japan, which he joined in 1999. His principle research interests are machine vision and image recognition. He is a member of IEICE IEEJ, IITE, IPSJ and JSPE.