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Restoration of Blurred Images Using Revised Bayesian-Based Iterative Method

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***Abstract*—A restoration method of degraded images based on the Bayesian-based iterative method is proposed. An iterative method is developed by regarding the observed degraded images as probabilities and point spread functions as the conditional probabilities. The restored images are estimated by using Bayesian rule. We have proposed two kinds of the iterative method. One is to use the observed images as the initial values of the estimated images when we estimate the point spread function. The other method is to estimate the initial values of the point spread function by using the logarithmic amplitude spectrum of the blurred image. The simulation results show that the proposed methods are effective to restore the blurred images.**

***Keywords*-$point\ spread\ function, Bayesian\ rule$**

I. INTRODUCTION

To make a clear image from degraded image, many enhancement techniques have been developed until now [1],[2],[3],[4],[5]. There are so many papers published until now about restoration algorithms. Those papers can be classified into two categories. One is a model-based approach [2],[3],[4] and the other is a learning-based approach.

The main technique for the former approach is to develop sharpness filters [2],[3]. More masks to approximate a derivative operation have been developed. By using the filters they could enhance the image. But they also enlarge pixel noise. The learning-based approach is to develop an iterative algorithm such that a criterion function could be minimized.

We adopt the second approach to enhance images by using the Bayesian rule. This method was first proposed by [5]. The Bayesian rule reflects optimal estimation in a sense to minimize the cost function under noisy observation and an iterative algorithm was proposed to find the optimal solution [6] and [7]. The algorithm include two parts, the first one is to estimate a point spread function from the estimated image and the second one is to estimate the original image by using the estimated point spread function. Thus, this algorithm might be optimal when the observed image is similar to the original image, that is, in case of a high S/N ratio. Therefore, the results will depend on the initial guesses of point spread function although the previous reports are assumed to be fixed [5],[6],[7].

In this paper, we propose two methods. One is to use the observation image instead of the estimated image when we estimate the point spread function (Algorithm I). The other method is to use an estimated point spread function as the initial guess of the point spread function in the Bayesian-based iterative procedure.

First, we will show the principle of the Bayesian-based iterative method proposed by Richardson [5]. Then, we will propose two methods. After that the simulation results are illustrated to show the effectiveness of the proposed methods.

II. PRINCIPLE OF IMAGE RESTORATION

In image enhancement, the ultimate goal of restoration techniques is to improve a given image in some sense. Restoration is a process that attempts to recover an image that has been degraded by using a priori knowledge of the degradation phenomenon. As shown in Fig. 1, the degradation process may be modeled as an operator $\mathbf{H}$ in case of noiseless situation. It operates on an input image $f(x, y)$ to produce a degraded image $g(x, y)$. For the sake of simplicity, we denote $f(x, y)$ by $f(x)$, $g(x, y)$ by $g(x)$, $h(x, y)$ by $h(x)$, etc. In equation form, we have

$$g(x) = \mathbf{H}f(x) = h * f(x) = \sum_{y=-\infty}^{\infty} h(x-y)f(y) \quad (1)$$

where $h(x)$ is an impulse response and * denotes the operation of convolution.

Based on the convolution theorem, the frequency domain representation of Eq. (1) becomes

$$G(j\omega) = H(j\omega)F(j\omega) \quad (2)$$

where $G(j\omega)$, $H(j\omega)$, and $F(j\omega)$ are Fourier transforms of $g(x)$, $h(x-y)$, and $f(y)$, respectively. As shown in Fig. 1, given $G(j\omega)$ and some knowledge about $H(j\omega)$, the objective of restoration techniques is to recover $F(j\omega)$ which means to recover the original image $f(x)$ via the inverse Fourier transform.

III. RICHARDSON'S ITERATIVE METHOD

We will review an iterative method by Richardson [5] in this section. Given the degraded image g, the point spread function h and the original image f are estimated based on Bayes' theorem. It will be effective to estimate the original image f from the observed image g. It was assumed that g, h, and f are discrete and are not necessarily normalized. The numerical values of g, h, and f are considered as measures of the frequency of the occurrence of them at those points. h is usually in normalized form. Energy of f originating at a point

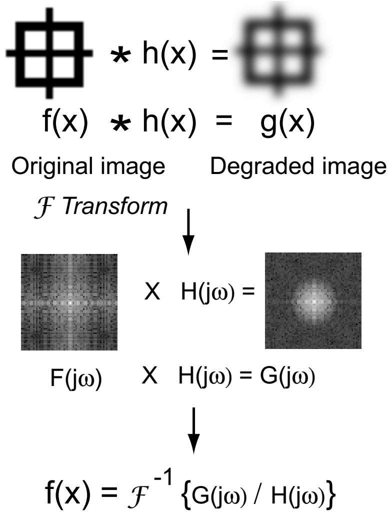

Fig. 1. The restoration principle.

is distributed as g at points according to the energy indicated by h. Thus, g represents the resulting sums of the energy of f originating at all points.

In the notation of this problem the usual form of the Bayes' theorem is stated as the conditional probability of f, given g. It was assumed that the degraded image g was of the form $g = h * f$, where * denotes the operation of convolution such that

$$g(x) = h * f(x) = \sum_{y=-\infty}^{\infty} h(x-y)f(y). \tag{3}$$

Note that f and g are intensity functions of the original image and observed image, respectively and h is the weighting function depending on image measurement devices. We assume that the input image and the weighting function are unknown. The values of f, g, and h are not limited within [0,1]. We normalize and denote them by f', g', and h'. Thus, we have

$$f'(x) = \frac{f(x)}{\sum_{x=-\infty}^{\infty} f(x)} = \frac{f(x)}{F} \tag{4}$$

$$g'(x) = \frac{g(x)}{\sum_{x=-\infty}^{\infty} g(x)} = \frac{g(x)}{G} \tag{5}$$

$$h'(x) = \frac{h(x)}{\sum_{x=-\infty}^{\infty} h(x)} = \frac{h(x)}{H} \tag{6}$$

where F,G, and H could be equal since the restoration process is conservative. Note that f, g, and h are nonnegative and the total sums are equal to one. Thus, we could regard them as probability measures and $f'(x_1)$ as the probability measure of the original image $f(x_1)$ at x_1. This means that the possibility of the existing intensity of the original image $f(x_1)$ at x_1. Similarly, $g'(x_2)$ and $h'(x_1)$ mean the possibility of the existing intensity of the observed image $g'(x_2)$ at x_2 and the possibility of the transition weight from the input image $f(x_1)$ at x_1 to the output image $g(x_2)$ at x_2. Therefore, we have

$$P(g(x_2)|f(x_1)) = P(h(x_2 - x_1)) = h'(x_2 - x_1). \tag{7}$$

The above relation can be derived by using the following relation.

$$\begin{aligned} P(g(x_2), f(x_1)) &= P(g(x_2)|f(x_1))P(f(x_1)) \\ &= P(h * f(x_2), f(x_1)) \\ &= P(h(x_2 - x_1), f(x_1)) \\ &= P(h(x_2 - x_1))P(f(x_1)) \end{aligned}$$

where we have used independence assumption between original image and restoration mechanism.

Using the Bayes' theorem we have

$$\begin{aligned} P(f(x)|g(x_2)) &= \frac{P(g(x_2)|f(x))P(f(x))}{\sum_{x_1=-\infty}^{\infty} P(g(x_2)|f(x_1))P(f(x_1))} \\ &= \frac{f'(x)h'(x_2 - x)}{\sum_{x_1=-\infty}^{\infty} f'(x_1)h'(x_2 - x_1)}. \end{aligned} \tag{8}$$

If we multiply the both sides of Eq. (8) by $P(g(x_2)) = g'(x_2)$ and take the summation with respect to x_2, we get

$$\begin{aligned} P(f(x)) &= f'(x) \\ &= f'(x) \sum_{x_2=-\infty}^{\infty} \frac{h'(x_2 - x)g'(x_2)}{\sum_{x_1=-\infty}^{\infty} f'(x_1)h'(x_2 - x_1)}. \end{aligned} \tag{9}$$

Considering $F = G = H$ and multiplying them both sides of the above equation, we have

$$f(x) = f(x) \sum_{x_2=-\infty}^{\infty} \frac{h(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} f(x_1)h(x_2 - x_1)}. \tag{10}$$

Using the above equation, Richardson[5] proposed the following recurrence procedure to find the original image $f(x)$.

$$\begin{aligned} f_{n+1}(x) &= f_n(x) \sum_{x_2=-\infty}^{\infty} \frac{h_n(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} h_n(x_2 - x_1)f_n(x_1)}, \\ n &= 0, 1, 2, \ldots. \end{aligned} \tag{11}$$

In order to derive the recursive equation of the point spread function $h(x)$, we will set $x_3 = x_2 - x$. Then from Eq. (8) we have

$$P(f(x_2 - x_3)|g(x_2)) = \frac{f'(x_2 - x_3)h'(x_3)}{\sum_{x_1=-\infty}^{\infty} f'(x_1)h'(x_2 - x_1)}. \tag{12}$$

Multiplying both sides of the above equation by $P(g(x_2)) = g'(x_2)$, we have

$$P(f(x_2-x_3)|g(x_2))P(g(x_2)) = g'(x_2)\frac{f'(x_2-x_3)h'(x_3)}{\sum_{x_1=-\infty}^{\infty} f'(x_1)h'(x_2-x_1)}. \tag{13}$$

Using the Bayes' rule, we have

$$\begin{aligned} &P(f(x_2-x_3)|g(x_2))P(g(x_2)) \\ &= P(f(x_2-x_3), g(x_2)) \\ &= P(g(x_2)|f(x_2-x_3))P(f(x_2-x_3)) \\ &= h'(x_3)f'(x_2-x_3). \end{aligned} \tag{14}$$

From Eqs. (14)and (14), we have

$$h'(x_3)f'(x_2-x_3) = g'(x_2)\frac{f'(x_2-x_3)h'(x_3)}{\sum_{x_1=-\infty}^{\infty} f'(x_1)h'(x_2-x_1)}. \tag{15}$$

Taking the summation of both sides of Eq. (15) with respect to x_2, using the relation of Eqs. (4), (5), and (6), and noting that

$$\sum_{x_2=-\infty}^{\infty} f'(x_2-x_3) = 1, \tag{16}$$

we have the following relation.

$$h(x) = h(x)\sum_{x_2=-\infty}^{\infty}\frac{f(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} f(x_1)h(x_2-x_1)}. \tag{17}$$

Thus, using the same recursive relation as Eq. (11), we have

$$h_{m+1}(x) = h_m(x)\sum_{x_2=-\infty}^{\infty}\frac{f_n(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} f_n(x_1)h_m(x_2-x_1)}. \tag{18}$$

In order to check the convergences of the recursive relations given by Eqs. (11) and (18), the following relations are used.

$$\sum_{x_2=-\infty}^{\infty}\frac{h(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} h(x_2-x_1)f_n(x_1)} = 1, \tag{19}$$

$$\sum_{x_2=-\infty}^{\infty}\frac{f(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} f(x_1)h(x_2-x_1)} = 1. \tag{20}$$

(21)

Thus, we use the following criteria to stop the iterations.

$$1-\epsilon < \sum_{x_2=-\infty}^{\infty}\frac{h_m(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} h_m(x_2-x_1)f_n(x_1)} < 1-\epsilon, \tag{22}$$

$$1-\epsilon < \sum_{x_2=-\infty}^{\infty}\frac{f_n(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} f_n(x_1)h_m(x_2-x_1)} < 1-\epsilon. \tag{23}$$

Using the above relations, Richardson has proposed the following iterative algorithm(Richardson's Iterative Method).

Step 1. Set $n = 0, m = 0$, the initial guesses of $h_0(x)$, and $f_0(x)$, and small positive number ϵ.

Step 2. Solve the following equations:

$$f_{n+1}(x) = f_n(x)\sum_{x_2=-\infty}^{\infty}\frac{h_m(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} h_m(x_2-x_1)f_n(x_1)} \tag{24}$$

$$h_{m+1}(x) = h_m(x)\sum_{x_2=-\infty}^{\infty}\frac{f_n(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} f_n(x_1)h_m(x_2-x_1)}. \tag{25}$$

Step 3. If the following inequalities hold

$$\left|\sum_{x_2=-\infty}^{\infty}\frac{h_m(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} h_m(x_2-x_1)f_n(x_1)}\right| < 1-\epsilon \tag{26}$$

and

$$\left|\sum_{x_2=-\infty}^{\infty}\frac{f_n(x_2-x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} f_n(x_1)h_m(x_2-x_1)}\right| < 1-\epsilon, \tag{27}$$

then stop, otherwise $n \leftarrow n+1, m \leftarrow m+1$ go to Step 2.

The above iteration has no proof of convergence that means the results obtained by the above iteration may result in the good results or may not.

IV. Proposed Algorithm I

In order to get better results compared with Richardson's algorithm, we consider a new method based on the property of degraded images such that the blurred images are similar to the original images. In the Richardson's algorithm, if the bad estimation of $h_m(x)$ at the beginning stage, corresponding recovered images would become different images. After obtaining the bad estimation of recovered images, estimation of the point spread function turns worse. As a result, the iteration will produce worse and worse estimation of the point spread function and recovered images. Assuming the degraded images are not so far from the original images, we use the blurred image to estimate the point spread function $h_m(x)$ instead of the recovered image that is the estimated image. Therefore, we have proposed the following steps:

Algorithm I

Step 1. Set $n = 0, m = 0$, small positive number ϵ, and $f_0(x) = g(x)$. Set the initial guesses of $h_0(x)$.

Step 2. Solve the following equations:

$$f_{n+1}(x) = f_n(x) \sum_{x_2=-\infty}^{\infty} \frac{h_m(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} h_m(x_2 - x_1)f_n(x_1)} \quad (28)$$

$$h_{m+1}(x) = h_m(x) \sum_{x_2=-\infty}^{\infty} \frac{f_n(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} g(x_1)h_m(x_2 - x_1)}. \quad (29)$$

Step 3. If the following inequalities hold

$$\left| \sum_{x_2=-\infty}^{\infty} \frac{h_m(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} h_m(x_2 - x_1)f_n(x_1)} \right| < 1 - \epsilon \quad (30)$$

and

$$\left| \sum_{x_2=-\infty}^{\infty} \frac{f_n(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} f_n(x_1)h_m(x_2 - x_1)} \right| < 1 - \epsilon, \quad (31)$$

then stop, otherwise $n \leftarrow n + 1$ and go to Step 2.

V. Variation Using the Reverse Function

We consider a more simple form of the proposed algorithm. We set the denominator of Eq. (38) by

$$L_{nm}(x_2) = \sum_{x_1=-\infty}^{\infty} h_m(x_2 - x_1)f_n(x_1). \quad (32)$$

It is the convolution sum between the original image $f_n(x_1)$ and the point spread function $h_m(x_2 - x_1)$. Therefore, if $L_{nm}(x_2) = g(x_2)$, then the estimated image $f_n(x_1)$ becomes the true original image. Furthermore, we have

$$f_{n+1}(x) = f_n(x) \sum_{x_2=-\infty}^{\infty} \frac{h_m(x_2 - x)g(x_2)}{L_{nm}(x_2)}. \quad (33)$$

We define $r_{nm}(x_2)$ by

$$r_{nm}(x_2) = \frac{g(x_2)}{L_{nm}(x_2)} \quad (34)$$

which means the ratio between the observed degraded image and the degraded image obtained by using the estimated point spread function. Then Eq. (33) becomes

$$f_{n+1}(x) = f_n(x) \sum_{x_2=-\infty}^{\infty} h_m(x_2 - x)r_{nm}(x_2). \quad (35)$$

We define the reverse function of $k(x)$ by $k(x) = h(-x)$. Then Eq. (33) becomes

$$f_{n+1}(x) = f_n(x) \sum_{x_2=-\infty}^{\infty} \frac{k_m(x_2 - x)g(x_2)}{L_{nm}(x_2)}. \quad (36)$$

If we represent the convolution sum by Fourier transform, we have

$$\begin{aligned} f_{n+1}(x) &= f_n(x)FT^{-1}(FT(k_m(x - x_2))FT(r_{nm}(x_2))) \\ &= f_n(x)FT^{-1}(K_m(j\omega)R_{nm}(j\omega)) \end{aligned} \quad (37)$$

where FT and FT^{-1} denote the Fourier transform and inverse Fourier transform. Since $K_m(j\omega) = H_m(-j\omega)$, we could save the computational time by half.

VI. Simulation Results of the Proposed Algorithm I

In order to show the effectiveness of the proposed method, we will consider gray image (Example 1)and two of color images(Example 2, Example 3). The computer specification used here is shown in TABLE I. In Example 1 the gray image of 64×64 was made using Photoshop. The color images of512×512 of Example 2 and Example 3 were cropped from the standard sample data of high-resolution color images [8]. The degraded images are made by using Gaussian filters with the standard deviation $\sigma = 3.3$. We used the stopping parameters of m and n when maximum iteration number k is given. In these simulations, we changed those parameters (m, n, k) as (10,100,10), (5,100,10), and (5,5,100). TABLE II shows simulation results for three cases with PSNR (Peak Signal-to-Noise Ratio) in case of Example 2. Fig. 2 shows the simulation results of the gray image with (10,100,10). From this Fig. 2 the proposed method restored a clearer image compared with the results of Richardson's method [5]. In Figs.3-10 we show the simulation results of Example 2 and Example 3 with images obtained from [8]. The original images are shown in Fig. 3 and Fig. 7. The degraded images are shown in Fig. 4 and Fig. 8. The restored images by [5] and the proposed method are shown in Fig. 5 and Fig. 9.

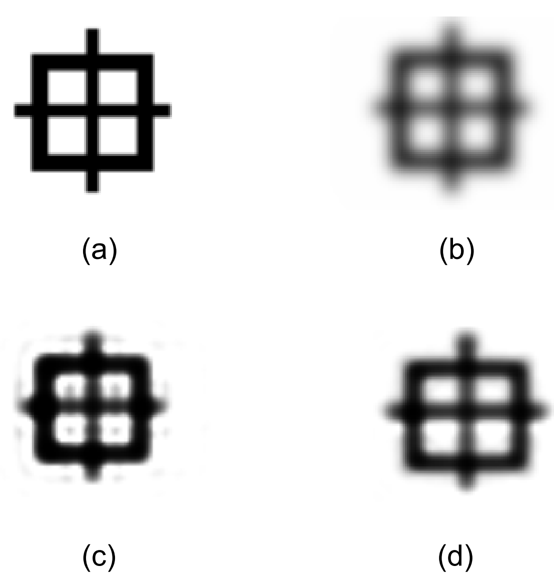

Fig. 2. The comparison for Example 1.

Fig. 3. Original image for Example 2: Cafeteria.

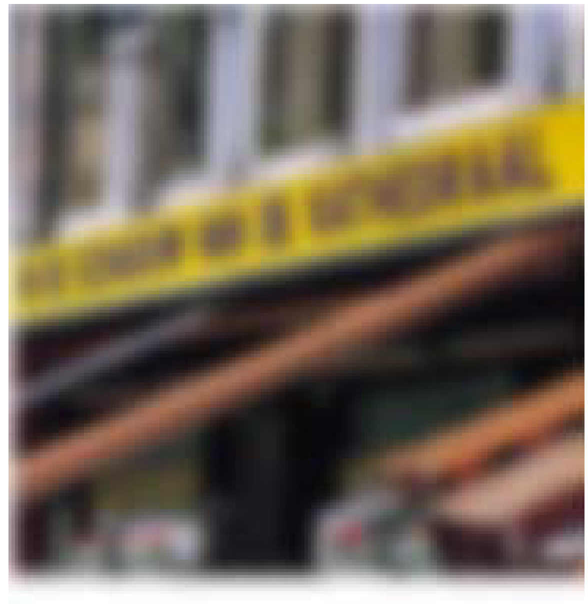

Fig. 4. Degraded image for Example 2.

Fig. 5. Richardson's method for Example 2.

Fig. 6. Proposed Algorithm I for Example 2.

TABLE I
COMPUTING ENVIRONMENT

OS	Windows XP
CPU	AMD Athlon(tm)64 X2 Dual Core
Memory	2GB

TABLE II
PSNR BETWEEN ORIGINAL IMAGE AND RESTORED IMAGE

Threshold value(m,n,k)	Degraded image	Richardson	Authors
(10,100,10)	14.5	15.7	16.6
(5,100,10)	14.5	16.5	16.0
(5,5,100	14.5	9.2	16.2

VII. PROPOSED ALGORITHM II

The above algorithm has some problems. One is a convergence problem for iteration. We must select a suitable initial function of the point spread function to obtain good results. The other problem is the speed of convergence. To solve these problems, we assume that the logarithmic amplitude spectrum of the point spread function is Gaussian distribution. This is

Fig. 7. Original image for Example 3: Fruits basket.

Fig. 8. Degraded image for Example 3.

Fig. 9. Richardson's image for Example 3.

Fig. 10. Proposed Algorithm I for Example 3.

based on the fact that the power spectrum of the point spread function is equi-uniform for each frequency. To speed up the computation to estimate the point spread function, we select a small area of the image where the low frequency seems to be dominant.

A. *Estimation of the Point Spread Function*

It is well-known that the spectrum of the point spread function includes the low frequencies compared with those of the original images. From Eq. (2) we can see that the spectra of the observed image are almost similar to the spectra of the point spread function. Thus, we can estimate the spectrum region of the point spread function from the blurred image (observed image). Since the major part of the low frequency region is affected by the zero frequency component, we adopt the logarithmic amplitude spectrum of the blurred image to remove the zero frequency. Thus, the computation process to estimate the point spread function is given by the following steps.

Step 1. Applying the Hamming window to the blurred image, find the logarithmic amplitude spectrum of the obtained image.

Step 2. Normalize the logarithmic amplitude spectrum within [0, 255] and threshold it with 128. The image is called a binary image.

Step 3. To remove the impulsive noise, apply 5×5 median filter to the binary image.

Step 4. Find the center of the binary image and determine the radius r by using the least mean squres method.

Step 5. Set $r = 3\sigma$ and find the Gaussian distribution function.

Step 6. Using inverse Fourier transform, find the point spread function $h(x)$.

To show the process stated above, we will use a sub-area

Fig. 11. The original image: Wine and tableware and sub-image to estimate the point spread function. Here, the sub-image is denoted by the square area and it is assumed to be known the point spread function with the spectrum as shown in the image.

of the original image with the known point spread function as shown in Fig. 11. Using this sub-image, we apply the procedure to an image given by Fig. 12.

B. Algorithm II

The estimate of the point spread function by using Step 1 to Step 6 is used as a rough estimate of the point spread function in order to converge the iteration algorithm in Algorithm I. Thus, Algorithm II is given by the following steps:

Step 1. Set $n = 0, m = 0$, small positive number ϵ. Furthermore, $f_0(x) = g(x)$ and $h_0(x) = h_p(x)$ where $h_p(x)$ denotes the estimated h(x) in the above Section.

Step 2. Solve the following equations:

$$f_{n+1}(x) = f_n(x) \sum_{x_2=-\infty}^{\infty} \frac{h_m(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} h_m(x_2 - x_1) f_n(x_1)} \quad (38)$$

$$h_{m+1}(x) = h_m(x) \sum_{x_2=-\infty}^{\infty} \frac{f_n(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} g(x_1) h_m(x_2 - x_1)}. \quad (39)$$

Step 3. If the following inequalities hold

$$\left| \sum_{x_2=-\infty}^{\infty} \frac{h_m(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} h_m(x_2 - x_1) f_n(x_1)} \right| < 1 - \epsilon \quad (40)$$

and

$$\left| \sum_{x_2=-\infty}^{\infty} \frac{f_n(x_2 - x)g(x_2)}{\sum_{x_1=-\infty}^{\infty} f_n(x_1) h_m(x_2 - x_1)} \right| < 1 - \epsilon, \quad (41)$$

then stop, otherwise $n \leftarrow n + 1$ and go to Step 2.

TABLE III
COMPUTING TIME

	Algorithm I	Algorithm II
Time [s]	38179.56	846.95

C. Speed-Up of Algorithm II

In order to speed up the algorithm, we should use the small size training image as shown in Fig. 11 instead of the full size image. the selection of the sub-image is the most important to obtain a better estimation of the point spread function. Since we can assume that he point spread function is the same even if the image sizes are different, we use a small size image instead of a large size image. We use images with 2560×2048 and select 256×256 to estimate the point spread function. The problem is where we should select the sub-images for training the point spread function. Estimation of Bayesian principle requires the broad band input data as in the system parameter identification to get the high performance. Thus, we select the high frequency images which include many edges. To find the edges, we use the Laplacian filter and take the area with large variance. Therefore, we select the sub-image area by the following steps:

Step 1. Apply the Laplacian filter to the observed image.

Step 2. Select the sub-image with 256×256.

Step 3. Find an area with the largest variance from the above sub-images.

By the above steps we will select the training area to estimate the point spread function stated in Section VII-A.

VIII. Simulation Results

We consider Cafeteria, Fruits and basket, and Wine and tableware whose true images are known in advance. After applying Algorithm I and Algorithm II to those images, we check the case where the true image is not obtained and the blurred images are taken by using a high resolution camera without adjusting so precisely which results in a little bit blurred images. We show the simulation results for the former case in Figs. 13-15 which are corresponding to Figs. 2, 7, and 11, respectively.

Compared with the restored images by Algorithm I, the restored images seem to be similar to the original ones. Furthermore, the computational time by Algorithm II is faster than that of AlgorithmI as shown in Table III.

Finally, we have applied Algorithm I and Algorithm II to the blurred images which are taken by using a high resolution camera. Here, we took artificially blurred images without auto-focus operation. Restored images are shown in Figs. 16 and 17. The case of high density camera makes clear images when the image scales are small. But if we enlarge them, then the difference become clear as shown in Fig. 17. From this result, the Algorithm II could be used to restore the blurred images.

IX. Conclusions

In this paper, methods of restoration of the degraded images by using the Bayesian-based iterative method are proposed.

The simulation results showed that the proposed method could restore the degraded images more clearly compared with the Richardson's method while the threshold values of (n, m, k) must be determined by trial and error.

Furthermore, the computation load has been decreased by half by introducing the ratio between the observed degraded image and the degraded image by using Algorithm I. Algorithm II could restore the blurred images more precisely and faster compared to Algorithm I since the latter method has only selected the initial image as the observed image without considering the initial guess of the point spread function.

Algorithm II takes more time to estimate the point spread function. But taking into consideration that the point spread function does not vary from place to place in the same image, we can select small region to estimate the function. In this paper, we select the sub-image where the variation of the image is rather high, that is, the image includes many edges. Since we took the sub-image with 256×256 size, it did not require so much time.

An open problem is that the Bayesian approach might not have a solution since the convergence of the iterative method has not been proved. But the initial guess may not be so far from the solution of the Bayesian equation since the blurred image structure will keep the similar behavior to the original images.

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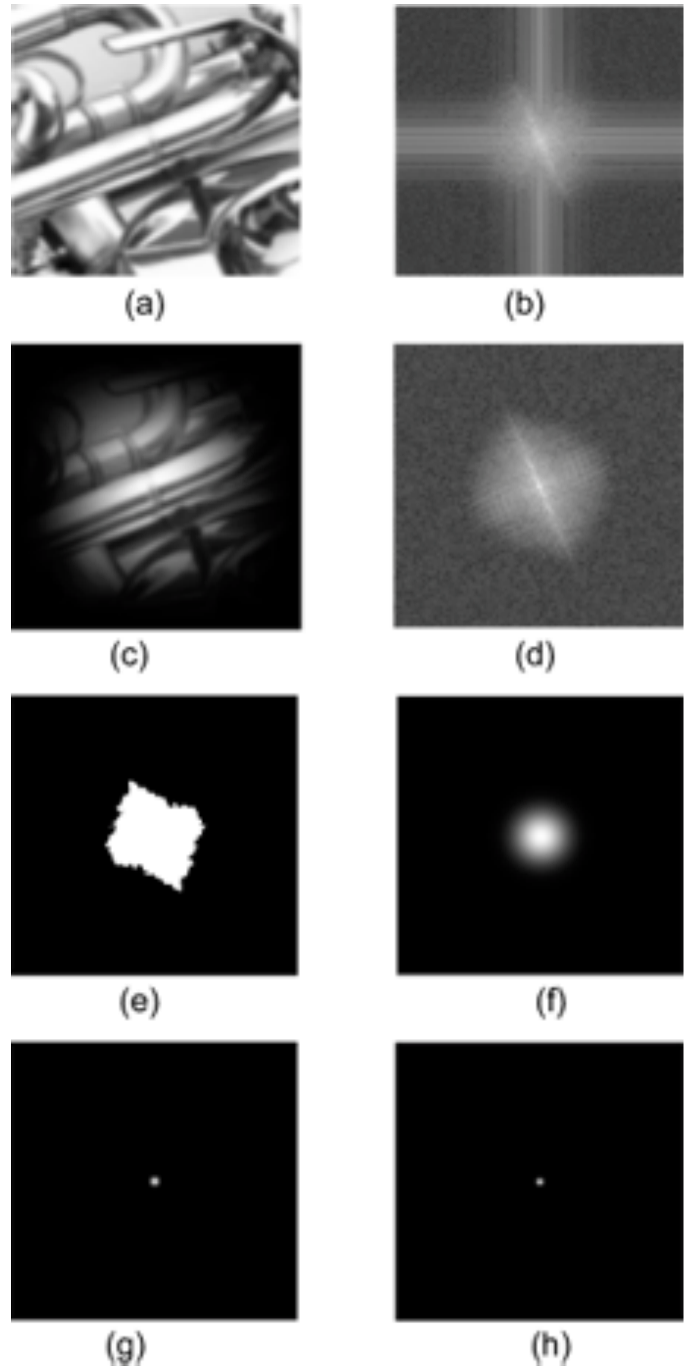


Fig. 12. The estimation process of the point spread function. Here, (a) is the blurred image denoted in Fig. 11, (b) is the logarithmic amplitude spectrum of (a), (c) is the blurred image filtered by the hamming window, (d) is the logarithmic amplitude spectrum of (c), (e) is the estimated logarithmic amplitude spectrum of (d) after processing of Step 2 and Step 3, (f) is estimated Gaussian distribution of (e) after processing Step 4 and Step 5, (g) is the estimated point spread function, and (h) is the true point spread function.

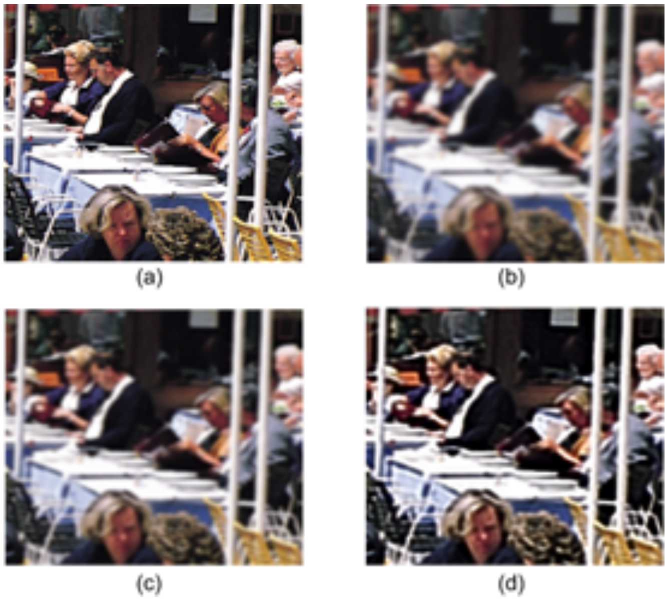


Fig. 13. The simulation results for the image: Cafeteria. Here, (a) is the original image, (b) is the blurred image, and (c) is the image by Argorithm I, and (d) is the image by Argorithm II.

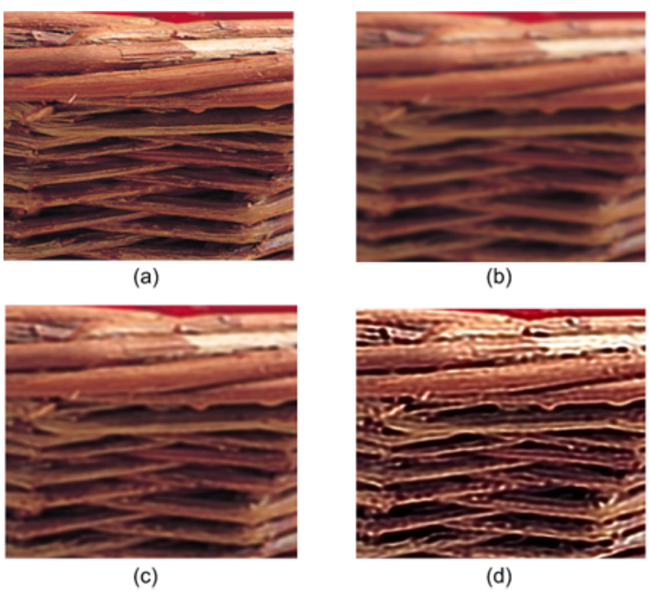


Fig. 14. The simulation results for the image: Fruits basket. Here, (a) is the original image, (b) is the blurred image, and (c) is the image by Argorithm I, and (d) is the image by Argorithm II.

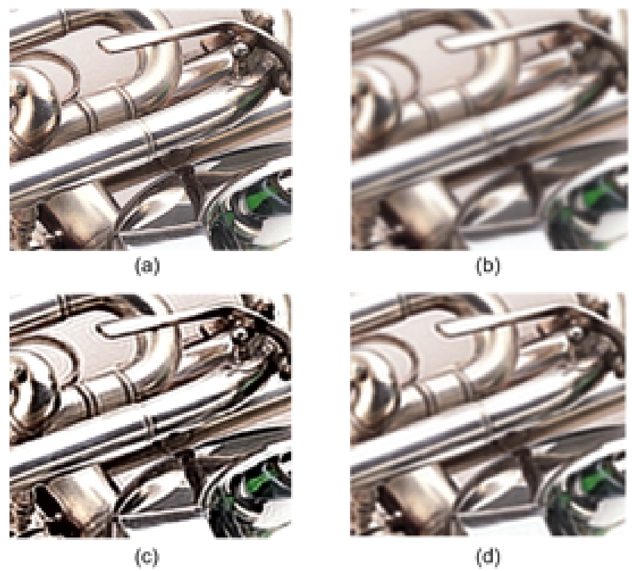
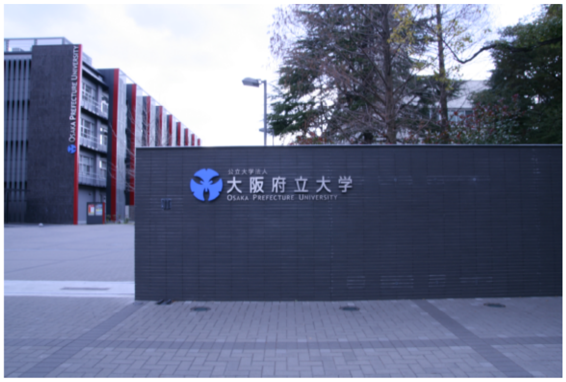
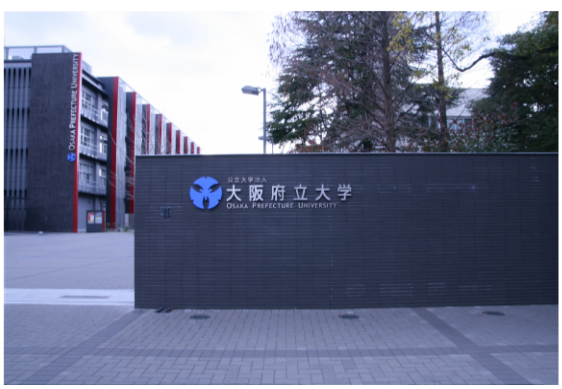


Fig. 15. The simulation results for the image: Wine and tableware. Here, (a) is the original image, (b) is the blurred image, and (c) is the image by Argorithm I, and (d) is the image by Argorithm II. known point spread function with the spectrum as shown in the image.



(a)

(b)



(c)

Fig. 16. The simulation results for the blurred image: Osaka Prefecture University. (a) is the blurred image, (b) is the image by Argorithm I, and (c) is the image by Argorithm II. known point spread function with the spectrum as shown in the image.

(a) Blurred image

(b) Algorithm I

(c) Algorithm II

Fig. 17. The comparison of the small area. (a) is the blurred image, (b) is the image by Argorithm I, and (c) is the image by Argorithm II.