# Blind Image Restoration Method by PCA-based Subspace Generation

Brian Sumali, Nozomu Hamada
Malaysia-Japan International Institute of Technology,
Universiti Teknologi Malaysia,
Kuala Lumpur, Malaysia
sbrian2@live.utm.my, hamada@utm.my

Yasue Mitsukura
Department of System Design Engineering
Faculty of Science and Technology, Keio University
Yokohama, Japan
mitsukura@sd.keio.ac.jp

***Abstract*—Principal Component Analysis (PCA) has been effectively applied for image restoration. Original idea underlying PCA approach has two different roots. One is from the fact that PCA is relevant to variance of pixel intensity by which the missing high frequency components in blurred image should be recovered. The other comes from the idea of source separation based on PCA. In the light of PCA approach we have proposed an image restoration algorithm which contains the following three novel aspects: iterative application of PCA, Gaussian smoothing filtering for image ensemble creation, and no-reference image quality index for iteration number management. This paper aims to investigate and propose a non-iterative PCA-based image restoration with some generalizations. First, through conducted experiments the variance of Gaussian filters as well as the number of created images by them are appropriately determined. Second, weights are introduced to the principal component images. Finally, optimal weights are determined by maximizing the image quality index with no reference. Experimental results by the proposed method provide higher PSNR than the previous iterative PCA approach.***

***Keywords*—Blind image restoration; Single image restoration; Principal component analysis; Gaussian blur; Image quality assessment**

## I. INTRODUCTION

In imaging an object and scene, degradations such as blur, noise, and other uncertain factors are inevitable. Image restoration aims to reconstruct an estimate of the original image from the degraded observation. Current image restoration techniques, known as blind image restoration methods try to solve this ill-posed inverse problem where the degradation process is unknown and information about the original image is not available. Generally, image degrading process is nonlinear and shift-variant, however in most of the applications it is assumed to be represented by linear convolution with shift invariant point spread function (PSF). Therefore this sort of blind restoration is a blind deconvolution. Its task is to separate two convolved signals, original image and PSF of degrading system when both signals are either unknown or partially unknown. Up to now numerous blind deconvolution algorithms have been developed in many fields, such as astronomy, remote sensing, medical imaging, and optics. The developed algorithm improved image quality without knowing exact image acquisition mechanism and complicated calibration. For conventional overview of blind image deconvolution, see [1] [2].

The basic approach for blind image restoration uses some physical properties of the original image and partial information about the degradation process. One approach tries to identify the PSF of degradation system separately from the original image. The other one incorporates the identification of the degradation PSF as well as deconvolution procedure. For example, iterative blind deconvolution method proposed by Ayers and Dainty [3] applies alternating estimation between the PSF and the original image under the image-domain constraints of non-negativity of image and PSF during iterations.

Most blind image restoration methods use particular PSF with small number of blurring parameters, such as out-of-focus blur, motion blur, and Gaussian blur, etc. Although these approaches are limited, but it makes the problem simpler and effective for the case that the assuming model sufficiently matches the real PSF. Some recent works are less restrictive but these still impose prior assumption for PSF. Yin et al. [4] proposed a method based on blind source separation technique in combination with genetic algorithm for blurring parameters optimization. The method by Almeida et al. [5] includes a learning technique which focuses the main edges of image and gradually takes details into account. Their method is applicable color images as well as hyperspectral images.

This paper is concerned about a single channel blind image restoration using PCA (Principal Component Analysis) under the assumption of Gaussian-like PSF blur. Previous works connecting PCA and blind image restoration have been proposed in [6]-[9]. In [6], Li et al. a deconvolution FIR filter with unity filter norm constrain is designed by maximizing variance of output image of the deconvolution filter. Their idea is based on that the lost high frequency component from the original image through blur process can be recovered by enhancing the variance of deconvolution filter output. Therefore, the application of PCA is relevant to the variance of image by which the lost high frequency components could be recovered. Their succeeding work by Li et al. [7] solved the problem to estimate the missing high frequency component also by detecting first principal component through PCA. Their first step is to create ensemble of images by shifting the degraded image horizontally as well as vertically. Then the first principal component of PCA is added to the degraded image as an estimate of the lost high frequency component through the blurring system. Their idea comes from the source separation scheme based only on 2nd-order statistics.

Both our previous approaches [8] and [9] have implemented the PCA but as a different scheme from [6] and [7]. The major difference is that the blurred ensemble images are generated by Gaussian smoothing filtering not by shifting as in [7]. Secondly, an iterative PCA algorithm is applied. Finally, a blind image quality assessment with no reference is introduced for managing the iteration number. Specifically, the natural image quality evaluator (NIQE) proposed by Mittal et al. [10] was applied.

Although this study is based on PCA for determining the high frequency component estimation in a same way as adopted in [8] and [9], some modifications have been done to improve the previous iterative PCA approach. The main flow of the procedure and novel contributions are shown below.

1) Creation of blurred images: For the given blurred image $(g_1)$, apply M-1 Gaussian filters with standard deviation of $j\sigma$ ($j$=1~M-1) respectively to obtain additional blurred images $(g_2, g_3, \cdots, g_M)$. This study provides an experimentally investigation about an appropriate selection of the parameters $(\sigma, M)$ at this process.

2) Apply PCA to the ensemble $\{g_i | i = 1 \sim M\}$ then obtain the first some principal components with zero average process beforehand.

3) Unlike other relevant studies, the proposed formulation of an estimate is the linear combination of the first some principal components obtained in 2). The weights of each components are determined from the first component up to the necessary order successively by maximizing the image quality assessment index NIQE. This novel linear combination formula and its determination algorithm may bring image recovery improvement, and it will be shown in some experiments.

The rest of this paper is structured as follows: In II, brief summary of conventional PCA-based image restoration methods and image quality index used here are described. The proposed method is proposed in Section III. Some experimental results are shown in IV, then the paper is concluded in V.

## II. PCA Approach for Image Restoration

### A. Mathematical Model

General mathematical model of a linear degradation caused by blurring is given by

$$g = h * f \tag{1}$$

where $f, g,$ and $h$ represent the original image, the blurred image, and the PSF of blurring system respectively. The operator $*$ represents two-dimensional convolution. In this study we restrict the blur PSF within Gaussian blur filters. In general, observation noise should be added to $g$, but it is ignored here.

The preliminary step in PCA implementation is to convert the convolution system Eq. (1) into its matrix-vector form:

$$\boldsymbol{g} = \boldsymbol{H}\boldsymbol{f} \tag{2}$$

where $\boldsymbol{H}$ denotes the blurring matrix, $\boldsymbol{f}$ and $\boldsymbol{g}$ denote column vector of the original and the blurred images respectively.

### B. Constrained Variance Maximization [6]

For the deconvolution or the inverse model of Eq. (1)

$$\hat{f} = g * w \tag{3}$$

with 2-dimensional FIR filter $w$ and its matrix-vector form

$$\hat{\boldsymbol{f}} = \boldsymbol{G}\boldsymbol{w} \tag{4}$$

where $\boldsymbol{G} = [\boldsymbol{g_1} \quad \boldsymbol{g_2} \quad \cdots \quad \boldsymbol{g_M}]$, $\boldsymbol{g}_i$ $(i = 2 \sim M)$ are shifted image of $\boldsymbol{g_1} = \boldsymbol{g}$, Li et al. [6] defined deconvolution problem as an optimization. The cost function accompanying constraint with respect to $\boldsymbol{w}$ are given by

$$J(\boldsymbol{w}) = var(\hat{\boldsymbol{f}}) \tag{5}$$

$$\|\boldsymbol{w}\| = 1 \tag{6}$$

respectively, where $var(\hat{\boldsymbol{f}})$ means the variance of $\hat{\boldsymbol{f}}$ which can measure high-frequency energy in some sense. From the PCA the deconvolution filter $\hat{\boldsymbol{w}}$ maximizing $J(\boldsymbol{w})$ is determined by

$$\hat{\boldsymbol{w}} = \boldsymbol{\mu_1} \tag{7}$$

where $\boldsymbol{\mu}_1$ is the first principal vector or the eigenvalue with the largest eigenvalue of the covariance matrix

$$\boldsymbol{C}_g = \boldsymbol{G}^T\boldsymbol{G} \tag{8}$$

Then the estimate of the original image is given by

$$\hat{\boldsymbol{f}} = \boldsymbol{G}\hat{\boldsymbol{w}} + \boldsymbol{\psi} = \boldsymbol{G}\boldsymbol{\mu}_1 + \boldsymbol{\psi} \tag{9}$$

where

$$\boldsymbol{\psi} = \frac{1}{M}\sum_{i=1}^{M} \boldsymbol{g}_i \tag{10}$$

### C. PCA with shifting blurred ensemble

According to [7], an ensemble of blurred images of $\{\boldsymbol{g}_i; i = 1 \sim M\}$ is created by shifted images of the blurred $\boldsymbol{g} = g(k, l)$, such as

$$\{\boldsymbol{g}_i\} = \{g[k - r, j - s] | (r, s) \in [-R, R] \times [-S, S]\} \tag{11}$$

where the index $i$ is related with 2-D index $(r, s)$ in particular mapping.

Compute the average image $\boldsymbol{\psi}$ of the ensemble $\{\boldsymbol{g}_i; i = 1 \sim M\}$ by Eq. (10), then define

$$\boldsymbol{\phi}_i = \boldsymbol{g}_i - \boldsymbol{\psi} \tag{12}$$

and the matrix

$$\boldsymbol{A} = [\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \cdots, \boldsymbol{\phi}_M] \tag{13}$$

Then the estimate of the original image is given by

$$\hat{\boldsymbol{f}} = \boldsymbol{v}_1 + \boldsymbol{\psi} \tag{14}$$

where $\boldsymbol{v}_1$ is the first principal eigenvector of the covariance

$$\boldsymbol{C}_{\phi} = \frac{1}{M}\boldsymbol{A}\boldsymbol{A}^{T} \tag{15}$$

### D. No-Reference Image Quality Assessment

Image Quality Assessment (IQA) is categorized into three: Full-Reference IQA (FR-IQA), Reduced-Reference IQA (RR-IQA), and No-Reference IQA (NR-IQA). Typically, FR-IQA algorithms [11]-[13] calculate the distance between a test image with a pristine version of the image. In RR-IQA, only partial information about the pristine image is available. Lastly, NR-IQA algorithms evaluate the image quality without any information about the pristine image.

NR-IQA algorithms estimate an image's quality by comparing it to their own training database. Based on the training, NR-IQA algorithms can be categorized into two: opinion-aware algorithms [14]-[16] which trained using a set of images and their corresponding human subjective scores, and opinion-unaware algorithms [10] [17]-[19] that requires no human subjective score.

In this paper, the weights of PCA components for the restoration are determined using the naturalness image quality evaluator (NIQE) [10] an opinion-unaware NR-IQA algorithm proposed by Mittal et al.

## III. Restoration by PCA-based Subspace

The following step is the proposed PCA approach.

1) Create M blurred ensemble by Gaussian filtering as follow.

$$\left.\begin{aligned} g_1 &= g \\ g_j &= g * b_{j-1}(\sigma) \qquad (j = 2\sim M) \end{aligned}\right\} \tag{16}$$

where $b_{j-1}(\sigma)$ is the PSF of Gaussian filter with standard deviation of $(j-1)\sigma$ $(j = 2\sim M)$.

2) Apply the same procedure mentioned in II.C for the ensemble $\{g_i;\ i = 1\sim M\}$ of (16), then we obtain a set of principal components $\{\boldsymbol{v}_i | i = 1\sim M\}$ whose order is according to their eigenvalue magnitudes.

3) An estimate of $\boldsymbol{f}$ in J-dimensional subspace spanned by $\{\boldsymbol{v}_i | i = 1\sim J\}$ can be represented by

$$\boldsymbol{f}_J = \sum_{j=1}^{J} \alpha_j \boldsymbol{v}_j + \boldsymbol{\psi} \tag{17}$$

A sub optimal $\alpha_j (j = 1\sim J)$ are found by the following maximization of the NIQE value of the estimate $\boldsymbol{f}_J$.

Optimal $\alpha_1$:

$$\hat{\alpha}_1 = \arg Max\ NIQE(\boldsymbol{f}_1) \tag{18}$$

Thus, we may define

$$\hat{\boldsymbol{f}}_1 = \hat{\alpha}_1 \boldsymbol{v}_1 + \boldsymbol{\psi} \tag{19}$$

Optimal $\alpha_j$ $(j \geq 2)$ by using $\{\alpha_k;\ k = 1\sim j-1\}$:

$$\hat{\alpha}_j = \arg Max\ NIQE(\boldsymbol{f}_j) \tag{20}$$

where

$$\boldsymbol{f}_j = \hat{\boldsymbol{f}}_{j-1} + \alpha_j \boldsymbol{v}_j + \boldsymbol{\psi} \tag{21}$$

Repeat the process above by updating $j \rightarrow j+1$ until j reaches J.

In the process 1) above, two parameters:

- The standard deviation (σ) of Gaussian filter
- The number (M) of blurred images

need to be properly determined. These characterize the M-dimensional subspace by which the principal components are derived. Generally, appropriate these two parameters would depend on next image therefore it should be empirically investigated. Next section discusses such experiment for this purpose.

## IV. Experiments and Discussions

Experiments are conducted to verify the restoration quality of proposed method. All experimental data presented here are processed using a typical processor: Intel® Xeon® E5-1607 v3 @3.10 GHz, MATLAB R2014b. Test images used for this experiment are obtained from USC-SIPI image database [20].

### A. Obtaining optimal parameters

The experimental design is as follows:

- Data collection

From test images, 30 images with varying sizes are randomly selected. These images are then converted to grayscale and blurred with Gaussian blur with σ = 1 ~ 2.5 to serve as degraded image to be restored with PCA algorithm with various parameters. The details of these parameters can be found on Table I. Afterwards, the Peak Signal-to-Noise Ratio (PSNR) and Structural SIMilarity (SSIM) [11] values of the restored image are retrieved. PSNR and SSIM are chosen because they represent mathematical error and human visual perception, respectively. Our objective is to find a pair of parameters that constantly give good restoration result. Constant result translates to having small standard deviation and good restoration result translates to high average value. Hence, a "good" pair of parameters should have high average value and small standard deviation, both in PSNR and SSIM. Since PSNR and SSIM values have different scale, the retrieved PSNR and SSIM values are normalized such that they are non-negative and their maximum value is 1. After normalization, the 'quality' of a (M,σ) can be determined with

$$QSSIM_{\sigma M} = \overline{SSIM_{\sigma M}} * (1 - std(SSIM_{\sigma M})) \tag{22}$$

$$QPSNR_{\sigma M} = \overline{SSIM_{\sigma M}} * (1 - std(PSNR_{\sigma M})) \tag{23}$$

$$Q_{\sigma M} = \frac{QSSIM_{\sigma M} + QPSNR_{\sigma M}}{2} \tag{24}$$

where $std(X)$ defines the standard deviation of $X$.

- Determining optimal parameters

The obtained experimental result (see Fig. 1) shows that the maximum overall quality (M-σ pair that give high PSNR and SSIM value for all images) is achieved when the ensemble creation parameters are σ = 0.4 and M = 13. Other candidates of these are σ = 0.5, M = 9 and σ = 0.6, M = 7.

TABLE I. DATA COLLECTION SETTINGS

| Ensemble Creation Parameters | |
|---|---|
| Blur Type | Gaussian blur |
| No. of images (M) | 2 ~ 15 |
| Blur severity (σ) | 0.3 ~ 1 |

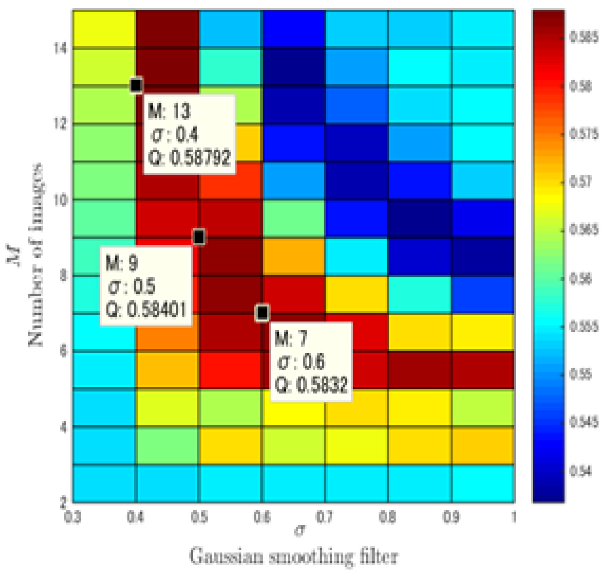



Fig. 1. Average value of normalized PSNR and SSIM with respect to

## B. Proposed Approach

Here, the proposed method is competed with blind adaptation of Lucy-Richardson method [21] [22], Levin's method [23], and iterative PCA. In all simulation, image size is 512x512 pixels. The input image is degraded by Gaussian blur with σ=1.0, 2.0, 9x9 support. Both the proposed and the iterative PCA method create an ensemble with Gaussian blur using optimal (M,σ) pair from the experiment above (i.e., σ=0.4 and M=13 are selected) with 7x7 support. The original PSF for blind LR method is Gaussian blur with σ=1, 9x9 support. The PSF size for Levin's method is 11x11. The obtained restoration results are shown in Fig. 2 and numerically compared in Table II.

We also applied the proposed method to a real blurred photo image acquired by Nokia Lumia 920 smartphone camera. The color image is then converted into grayscale (Fig. 3(a)) to be restored. The restored results are shown in Fig.3 (b: blind LR method), (c: Levin's method), (d: iterative PCA method) and (e: proposed method). The results show that our proposed method copes with even in real environments condition and yields better performance than other previous methods.

## C. Performance of NIQE

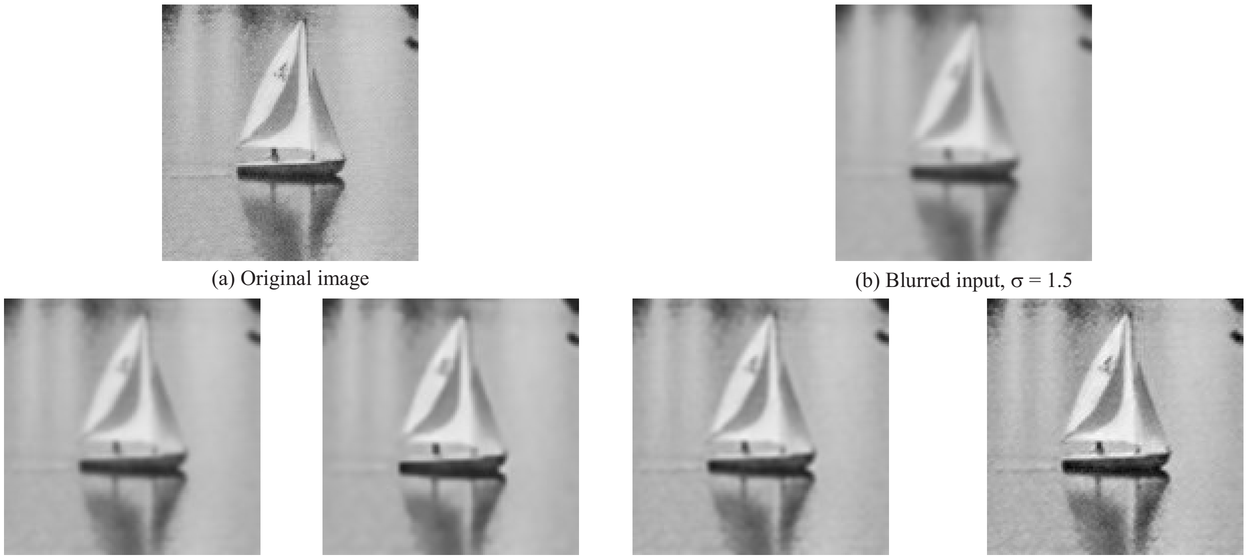
The performance of NIQE is evaluated by retrieving PSNR and NIQE index of an image restored with proposed method. Here, the input image is blurred by Gaussian blur with σ = 2, 9x9 support and the observed scalar is for the first principal component. The results are shown in Fig. 4, where the difference between optimal scalar according to PSNR and NIQE significantly differs. Since low NIQE value is equivalent to high image quality, the displayed graph of NIQE is reversed for comparison purpose. Obtaining image quality index that coincides with PSNR is future work to be solved.

# V. CONCLUSIONS

This paper proposed a blind image restoration method based on PCA approach. The proposed algorithm contains three main procedures: Gaussian filtering for creating ensemble images, PCA for subspace generation, and optimal estimation in the subspace by maximizing non-reference image quality index. In the first process we conducted an experiment and examined the results for determining appropriate parameters the standard deviation and the number of Gaussian filtering. Unlike other previous PCA-based approaches, a linear combination of the basis in the subspace is used for restoration estimates and the weights of it are recursively found by maximizing NIQE value. Experimental results by our method and other conventional algorithms show that the proposed restoration algorithm performs well in terms of PSNR as well as SSIM. The restoration results for real blurred images also show high performance of our approach. Due to no prior information on original image the image quality index adopted in the optimal estimation process is a key function in the proposed restoration scenario. In addition, though the blur operation in this study is restricted within a symmetric Gaussian low pass blur, the same restoration principle should be generalized to other types of blur such as motion blur.

TABLE II. COMPARISON OF PSNR AND SSIM

| | | Input | | Blind LR [21] [22] | | Levin, et al [23] | | Iterative PCA [9] | | Proposed method | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | PSNR [dB] | SSIM | PSNR [dB] | SSIM | PSNR [dB] | SSIM | PSNR [dB] | SSIM | PSNR [dB] | SSIM |
| Aircraft | σ = 1 | 31.20 | 0.9352 | 33.03 | 0.9602 | 26.24 | 0.8796 | 35.24 | 0.9761 | 39.86 | 0.9888 |
| | σ = 2 | 26.29 | 0.8284 | 27.20 | 0.8484 | 28.85 | 0.8808 | 30.47 | 0.9154 | 30.05 | 0.8988 |
| Lena | σ = 1 | 33.20 | 0.9142 | 35.35 | 0.9402 | 24.59 | 0.7854 | 36.71 | 0.9642 | 34.21 | 0.9662 |
| | σ = 2 | 28.62 | 0.8202 | 28.93 | 0.8244 | 28.58 | 0.8365 | 33.01 | 0.9052 | 34.76 | 0.9130 |
| Mandrill | σ = 1 | 23.72 | 0.7021 | 26.09 | 0.8598 | 21.38 | 0.5796 | 24.57 | 0.7608 | 25.52 | 0.8121 |
| | σ = 2 | 21.21 | 0.4493 | 21.56 | 0.4933 | 21.72 | 0.5069 | 22.90 | 0.6495 | 22.58 | 0.6149 |



(a) Original image

(b) Blurred input, σ = 1.5

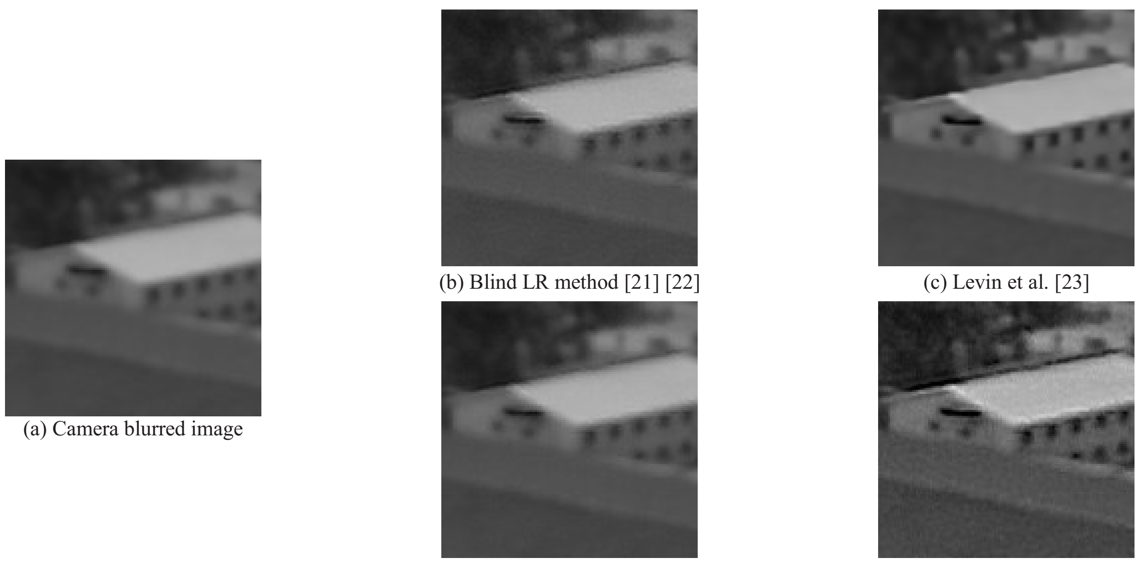
(c) Blind LR [21] [22]

(d) Levin, et al. [23]

(e) Iterative PCA method [9]

(f) Proposed method

Fig. 2. Simulated blur and its restoration result



(a) Camera blurred image

(b) Blind LR method [21] [22]

(c) Levin et al. [23]

(d) Iterative PCA method [9]

(e) Proposed method

Fig. 3. Real blurred image and its restoration result

## ACKNOWLEDGMENT

B. Sumali would like to thank the JAIF (Japan-ASEAN Integration Fund) in MJIIT for supporting to pursue this study.

## REFERENCES

[1] D. Kundur and D. Hatzinakos, "Blind image deconvolution," IEEE Signal Processing Magazine, vol.13, no.3, pp.43–64, May 1996

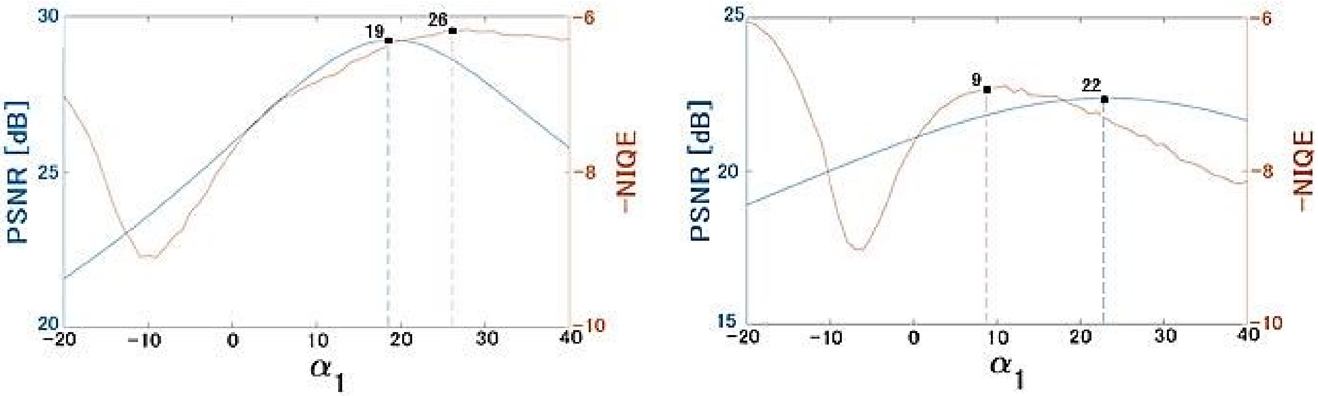
[2] D. Kundur and D. Hatzinakos, "Blind image deconvolution revisited," IEEE Signal Processing Magazine, vol.13, no.6, pp.61–63, Nov 1996

[3] G. R. Ayers and J. C. Dainty, "Iterative blind deconvolution method and its applications," Optics Letters, vol. 13(7), pp. 547–549, July 1988.

[4] H. Yin and I. Hussain, "Blind Source Separation and Genetic Algorithm for Image Restoration," International Conference on Advances in Space Technologies, Sept. 2006

[5] M. S. C. Almeida and L. B. Almeida, "Blind and Semi-Blind Deblurring of Natural Images", IEEE Transactions on Image Processing, pp. 36–52 Volume: 19, Issue: 1, Jan. 2010

[6] Dalong Li, S. Simske, and R. M. Mersereau, "Blind image deconvolution using constrained variance maximization," Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers, vol.2, pp.1762–1765 Vol.2, 7-10 Nov. 2004




(a) Aircraft σ = 2

(b) Mandrill σ = 2

Fig. 4. Comparison of PSNR and NIQE performance for determining the weight of first principal component

[7] Dalong Li, R. M. Mersereau, and S. Simske, “Atmospheric Turbulence-Degraded Image Restoration Using Principal Components Analysis,” IEEE Geoscience and Remote Sensing Letters, vol.4, no.3, pp.340–344, July 2007

[8] R. Nakamura, Y. Mitsukura, and N. Hamada, “Iterative PCA approach for blind restoration of single blurred image,” International Symposium on Intelligent Signal Processing and Communications Systems (ISPACS), pp.543–546, 12-15 Nov. 2013

[9] R. Nakamura, Y. Mitsukura, and N. Hamada, “Blind restoration of single-channel image using iterative PCA,” IEEE Conference on Systems, Process & Control (ICSPC), pp.84–87, 13-15 Dec. 2013

[10] A. Mittal, R. Soundararajan, and A. C. Bovik, “Making a "Completely Blind" Image Quality Analyzer,” IEEE Signal Processing Letters, vol.20, no.3, pp.209–212, March 2013

[11] Zhou Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, “Image quality assessment: from error visibility to structural similarity,” IEEE Transactions on Image Processing, vol.13, no.4, pp.600–612, April 2004

[12] Lin Zhang, Lei Zhang, Xuanqin Mou, and David Zhang, “FSIM: a feature similarity index for image quality assessment”, IEEE Transactions on Image Processing, vol. 20, no. 8, pp. 2378–2386, Aug. 2011

[13] Z. Wang, E.P. Simoncelli, and A. C. Bovik, “Multiscale structural similarity for image quality assessment,” Conference Record of the Thirty-Seventh Asilomar Conference on Signals, Systems and Computers, vol.2, pp.1398–1402 Vol.2, 9-12 Nov. 2003.

[14] A. Mittal, A. K. Moorthy, and A. C. Bovik, “No-Reference Image Quality Assessment in the Spatial Domain,” IEEE Transactions on Image Processing, vol.21, no.12, pp.4695–4708, Dec. 2012

[15] A. K. Moorthy and A. C. Bovik, “Blind Image Quality Assessment: From Natural Scene Statistics to Perceptual Quality,” IEEE Transactions on Image Processing, vol.20, no.12, pp.3350–3364, Dec. 2011

[16] M. A. Saad, A. C. Bovik, and C. Charrier, “Blind Image Quality Assessment: A Natural Scene Statistics Approach in the DCT Domain,” IEEE Transactions on Image Processing, vol.21, no.8, pp.3339–3352, Aug. 2012

[17] A. Mittal, G. S. Muralidhar, J. Ghosh, and A. C. Bovik, “Blind Image Quality Assessment Without Human Training Using Latent Quality Factors,” IEEE Signal Processing Letters, vol.19, no.2, pp.75–78, Feb. 2012

[18] Wufeng Xue, Lei Zhang, and Xuanqin Mou, “Learning without Human Scores for Blind Image Quality Assessment,” IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp.995–1002, 23-28 June 2013

[19] Lin Zhang, Lei Zhang, and A. C. Bovik, “A Feature-Enriched Completely Blind Image Quality Evaluator,” IEEE Transactions on Image Processing, vol.24, no.8, pp.2579–2591, Aug. 2015

[20] A. G. Weber, The USC-SIPI Image database version 5, “Signal and image Processing Institute”, Oct. 1997. http://sipi.usc.edu/database/database.php

[21] L. Lucy, “An iterative technique for the rectification of observed distribution,” Astron. J., vol. 79, no. 6, pp. 745–754, 1974.

[22] W. H. Richardson, “Bayesian-based iterative method of image restoration,” J. Opt. Soc. Amer. A, Opt. Image Sci., vol. 62, no. 1, pp.55–59,1972.

[23] A. Levin, Y. Weiss, F. Durand, and W. T. Freeman, “Efficient marginal likelihood optimization in blind deconvolution,” IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp.2657–2664, 20-25 June 2011