PERCEPTUALLY OPTIMIZED SUBSPACE ESTIMATION FOR MISSING TEXTURE RECONSTRUCTION

Takahiro Ogawa and Miki Haseyama

Graduate School of Information Science and Technology, Hokkaido University
N-14, W-9, Kita-ku, Sapporo, Hokkaido, 060-0814, Japan
E-mail: ogawa@lmd.ist.hokudai.ac.jp, miki@ist.hokudai.ac.jp

ABSTRACT

This paper presents a perceptually optimized subspace estimation method for missing texture reconstruction. The proposed method calculates the optimal subspace of known patches within a target image based on structural similarity (SSIM) index instead of calculating mean square error (MSE)-based eigenspace. Furthermore, from the obtained subspace, missing texture reconstruction whose results maximize the SSIM index is performed. In this approach, the non-convex maximization problem is reformulated as a quasi convex problem, and the reconstruction of the missing textures becomes feasible. Experimental results show that our method overcomes previously reported MSE-based reconstruction methods.

Index Terms— Image restoration, image texture analysis, interpolation, image quality assessment.

1. INTRODUCTION

Traditionally, many researchers have intensively studied missing texture reconstruction since it affords a number of fundamental applications. In recent works, Criminisi et al. proposed an exemplar-based fill-in approach as a representative method in this research field [1]. From a characteristic that the reconstruction of missing areas is one of the inverse problem, several methods using low-dimensional subspaces for deriving the inverse projection to estimate missing intensities have been proposed. For example, Amano et al. proposed an effective PCA-based method that estimated missing textures by back projection for lost pixels [2]. Furthermore, sparse representation-based image reconstruction has recently been studied. Mairal et al. proposed a representative work based on the sparse-representation [3], and Xu et al. also presented an improved exemplar-based method using the sparse representation [4].

It should be noted that in the previous works, they mostly try to calculate subspaces such as eigenspaces and subspaces based on the sparse representation, which minimize the mean square error (MSE). Although the MSE is the most popular metric used as a quality measure, it has been reported that MSE optimal algorithms do not necessarily produce images of high visual quality. Thus, the reconstruction using MSE-based subspaces tends not to be suitable. Recently, the structural similarity (SSIM) index [5] has been proposed as a representative measure in the field of image quality assessment. Furthermore, it has been reported that the SSIM index is superior to the MSE and its variants for measuring image qualities. Therefore, by using the SSIM index, calculation of subspaces which enable successful reconstruction of missing textures can be expected.

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In this paper, we present an SSIM-based optimal subspace estimation method for missing texture reconstruction. The proposed method uses the SSIM index as a new criterion for estimating the subspace to reconstruct missing areas within the target image. Specifically, we adopt the following two approaches: 1) SSIM-based calculation of optimal bases for known patches within the target image and 2) Reconstruction of missing textures based on a maximization problem of the SSIM index. Note that the first approach provides the perceptually optimized subspace for the following SSIM-based reconstruction approach. Furthermore, the second approach adopts a new scheme, and a non-convex maximization problem for reconstructing missing textures is reformulated as a quasi convex problem. Then we can derive the optimal solution based on the SSIM index, and successful reconstruction of the missing textures is expected.

2. SSIM INDEX

The SSIM index was proposed as a similarity between two vectors $\mathbf{x}$ and $\mathbf{y}$ ($\in \mathbf{R}^n$), and its simplified definition is shown as follows:

$$\mathrm{SSIM}(\mathbf{x},\mathbf{y}) = \frac{\left(2\mu_{\mathbf{x}}\mu_{\mathbf{y}} + C_1\right)\left(2\sigma_{\mathbf{x},\mathbf{y}} + C_2\right)}{\left(\mu_{\mathbf{x}}^2 + \mu_{\mathbf{y}}^2 + C_1\right)\left(\sigma_{\mathbf{x}}^2 + \sigma_{\mathbf{y}}^2 + C_2\right)}, \tag{1}$$

where $\mu_{\mathbf{x}}$ and $\mu_{\mathbf{y}}$ are respectively the means of $\mathbf{x}$ and $\mathbf{y}$, $\sigma_{\mathbf{x}}^2$ and $\sigma_{\mathbf{y}}^2$ are respectively the variances of $\mathbf{x}$ and $\mathbf{y}$. Furthermore, $\sigma_{\mathbf{x},\mathbf{y}}$ is the cross covariance between $\mathbf{x}$ and $\mathbf{y}$. The constants C_1 and C_2 are necessary for avoiding instability when the denominators are very close to zero. As shown in [5], the SSIM index is consistent with luminance and contrast masking, and the correlation.

3. SSIM-BASED OPTIMAL SUBSPACE ESTIMATION FOR IMAGE RECONSTRUCTION

In this section, we present an SSIM-based optimal subspace estimation method for the missing texture reconstruction. In the proposed method, a patch f ($w \times h$ pixels) including missing areas is clipped from the target image, and its missing textures are estimated from the other known areas. For the following explanations, we respectively denote two areas whose intensities are known and unknown within the target patch f as $\bar{\Omega}$ and Ω. Furthermore, we also define vectors, whose elements are respectively intensities within f and $\bar{\Omega}$, as $\mathbf{x}(\in \mathbf{R}^{wh})$ and $\mathbf{y}(\in \mathbf{R}^{N_{\bar{\Omega}}})$, where $N_{\bar{\Omega}}$ is the number of pixels within the area $\bar{\Omega}$.

First, the proposed method performs the SSIM-based optimal subspace estimation (See **3.1**). Furthermore, by using the obtained subspace, we derive the representation model optimized for the target patch f in terms of the SSIM index to reconstruct the missing area Ω (See **3.2**).

3.1. SSIM-Based Optimal Subspace Estimation

In our method, we first clip known patches f_i ($i = 1, 2, \cdots, L$) whose size is $w \times h$ pixels from the target image in the same interval. For the following explanation, two vectors $\mathbf{x}_i$ ($\in \mathbf{R}^{wh}$) and $\mathbf{y}_i$ ($\in \mathbf{R}^{N_{\bar{\Omega}}}$), which respectively correspond to $\mathbf{x}$ and $\mathbf{y}$, are defined for each patch f_i. From the clipped patches, we calculate an M-dimensional optimal subspace based on the SSIM index, where M should be a much smaller value than wh. Unfortunately, the bases of the subspace optimized in terms of the SSIM index do not become orthogonal, and thus, the proposed method adopts the simplest algorithm which computes the optimal bases one-by-one. In the rest of this subsection, the details of t-th ($t = 1, 2, \cdots, M$) optimal basis calculation are shown.

In t-th iteration, i.e., t-th optimal basis calculation, we first define the following vector approximating $\mathbf{x}_i$ ($i = 1, 2, \cdots, L$):

$$\begin{aligned} \mathbf{x}_i^{(t)} &= \begin{bmatrix} \hat{\mathbf{E}}^{(t-1)} & \mathbf{e}^{(t)} \end{bmatrix} \begin{bmatrix} \mathbf{a}_i^{(t-1)} \\ a_i^{(t)} \end{bmatrix} \\ &= \mathbf{E}^{(t)} \mathbf{a}_i^{(t)}, \end{aligned} \tag{2}$$

where $\hat{\mathbf{E}}^{(t-1)} = [\hat{\mathbf{e}}^{(1)}, \hat{\mathbf{e}}^{(2)}, \cdots, \hat{\mathbf{e}}^{(t-1)}]$ is a fixed $wh \times (t-1)$ matrix which contains $t-1$ bases previously calculated in $t-1$ iterations. Furthermore, $\mathbf{E}^{(t)} = \begin{bmatrix} \hat{\mathbf{E}}^{(t-1)} & \mathbf{e}^{(t)} \end{bmatrix}$, and $\mathbf{a}_i^{(t)} = \begin{bmatrix} \mathbf{a}_i^{(t-1)\prime} & a_i^{(t)} \end{bmatrix}'$ ($\in \mathbf{R}^t$) is a coefficient vector for obtaining $\mathbf{x}_i^{(t)}$. Note that vector/matrix transpose is defined by the superscript $'$ in this paper. We estimate the optimal basis $\hat{\mathbf{e}}^{(t)}$ of $\mathbf{e}^{(t)}$ which provides the optimal representation performance for all known patches f_i ($i = 1, 2, \cdots, L$) based on the SSIM index. The details are shown below.

The proposed method calculates the optimal basis $\hat{\mathbf{e}}^{(t)}$ by the following equation:

$$\left\{\hat{\mathbf{e}}^{(t)}, \hat{\mathbf{a}}^{(t)}\right\} = \arg\max_{\mathbf{e}^{(t)}, \mathbf{a}^{(t)}} \sum_{i=1}^{L} \mathrm{SSIM}(\mathbf{x}_i, \mathbf{x}_i^{(t)}) \quad \text{subject to} \quad \|\mathbf{e}^{(t)}\| = 1, \tag{3}$$

where $\mathbf{a}^{(t)}$ is a set of $\mathbf{a}_1^{(t)}, \mathbf{a}_2^{(t)}, \cdots, \mathbf{a}_L^{(t)}$, and $\mathrm{SSIM}(\mathbf{x}_i, \mathbf{x}_i^{(t)})$ is defined as follows:

$$\mathrm{SSIM}(\mathbf{x}_i, \mathbf{x}_i^{(t)}) = \left(\frac{2\mu_{\mathbf{x}_i}\mu_{\mathbf{x}_i^{(t)}} + C_1}{\mu_{\mathbf{x}_i}^2 + \mu_{\mathbf{x}_i^{(t)}}^2 + C_1}\right)\left(\frac{2\sigma_{\mathbf{x}_i, \mathbf{x}_i^{(t)}} + C_2}{\sigma_{\mathbf{x}_i}^2 + \sigma_{\mathbf{x}_i^{(t)}}^2 + C_2}\right). \tag{4}$$

In the above equation, $\mu_{\mathbf{x}_i}$ and $\mu_{\mathbf{x}_i^{(t)}}$ are respectively the means of $\mathbf{x}_i$ and $\mathbf{x}_i^{(t)}$, $\sigma_{\mathbf{x}_i}^2$ and $\sigma_{\mathbf{x}_i^{(t)}}^2$ are respectively the variances of $\mathbf{x}_i$ and $\mathbf{x}_i^{(t)}$, and $\sigma_{\mathbf{x}_i, \mathbf{x}_i^{(t)}}$ is the cross covariance between $\mathbf{x}_i$ and $\mathbf{x}_i^{(t)}$. Note that from Eqs. (2) and (4), we can see that the cost function in Eq. (3) is a function of $\mathbf{e}^{(t)}$ and $\mathbf{a}_i^{(t)}$ ($i = 1, 2, \cdots, L$). Therefore, the proposed method calculates the optimal basis $\hat{\mathbf{e}}^{(t)}$ and the optimal coefficient vectors $\hat{\mathbf{a}}_i^{(t)}$ ($i = 1, 2, \cdots, L$) by applying the constrained steepest ascend algorithm to Eq. (3). It is well known that the steepest ascend algorithm cannot necessarily provide the globally optimal solution in Eq. (3), but this algorithm can save the computation cost compared to the algorithm shown in the following subsection. From this reason, we utilize this scheme in the proposed method. By iterating the above procedures M times, we can obtain the optimal M bases $\hat{\mathbf{E}} = [\hat{\mathbf{e}}_1, \hat{\mathbf{e}}_2, \cdots, \hat{\mathbf{e}}_M]$ based on the SSIM index.

3.2. Missing Area Reconstruction Algorithm

In this subsection, the reconstruction algorithm of the missing area Ω within f is presented. The proposed method tries to estimate the optimal linear combination

$$\hat{\mathbf{x}} = \hat{\mathbf{E}}\hat{\mathbf{a}} \tag{5}$$

of the unknown vector $\mathbf{x}$ of f, where

$$\{\hat{\mathbf{x}}, \hat{\mathbf{a}}\} = \arg\max_{\mathbf{x}, \mathbf{a}} \mathrm{SSIM}\left(\mathbf{x}, \hat{\mathbf{E}}\mathbf{a}\right) \quad \text{subject to} \quad \mathbf{\Sigma}\mathbf{x} = \mathbf{y}, \tag{6}$$

and $\mathbf{\Sigma}$ is a matrix extracting only the known intensities in $\bar{\Omega}$. In the above equation,

$$\begin{aligned} \mathrm{SSIM}\left(\mathbf{x}, \hat{\mathbf{E}}\mathbf{a}\right) &= \left[\frac{2\mu_{\mathbf{x}}\mu_{\hat{\mathbf{E}}\mathbf{a}} + C_1}{\mu_{\mathbf{x}}^2 + \mu_{\hat{\mathbf{E}}\mathbf{a}}^2 + C_1}\right]\left[\frac{2\sigma_{\mathbf{x}, \hat{\mathbf{E}}\mathbf{a}} + C_2}{\sigma_{\mathbf{x}}^2 + \sigma_{\hat{\mathbf{E}}\mathbf{a}}^2 + C_2}\right] \\ &= \left[\frac{2\left(\frac{1}{wh}\mathbf{1}'\mathbf{x}\right)(\boldsymbol{\mu}_{\hat{\mathbf{E}}}'\mathbf{a}) + C_1}{\left(\frac{1}{wh}\mathbf{1}'\mathbf{x}\right)^2 + (\boldsymbol{\mu}_{\hat{\mathbf{E}}}'\mathbf{a})^2 + C_1}\right] \\ &\quad \times \left[\frac{2\mathbf{x}'\mathbf{H}\hat{\mathbf{E}}\mathbf{a} + whC_2}{\mathbf{x}'\mathbf{H}\mathbf{x} + \mathbf{a}'\hat{\mathbf{E}}'\mathbf{H}\hat{\mathbf{E}}\mathbf{a} + whC_2}\right], \end{aligned} \tag{7}$$

and

$$\boldsymbol{\mu}_{\hat{\mathbf{E}}} = \frac{1}{wh}\hat{\mathbf{E}}'\mathbf{1}, \tag{8}$$

where $\mathbf{1} = [1, 1, \cdots, 1]'$ is a $wh \times 1$ vector. Furthermore,

$$\mathbf{H} = \mathbf{I} - \frac{1}{wh}\mathbf{1}\mathbf{1}' \tag{9}$$

is a $wh \times wh$ centering matrix, where $\mathbf{I}$ is the identity matrix.

Since Eq. (7) is a nonconvex function of $\mathbf{x}$ and $\mathbf{a}$, we introduce the calculation scheme shown in [6]. First, we note the first term in Eq. (7) is a function only of $\frac{1}{wh}\mathbf{1}'\mathbf{x}\,(=\rho)$ and $\boldsymbol{\mu}_{\hat{\mathbf{E}}}'\mathbf{a}\,(=\omega)$. Thus, the problem in Eq. (6) is rewritten as follows:

$$\max_{\mathbf{x}, \mathbf{a}} \left(\frac{2\mathbf{x}'\mathbf{H}\hat{\mathbf{E}}\mathbf{a} + whC_2}{\mathbf{x}'\mathbf{H}\mathbf{x} + \mathbf{a}'\hat{\mathbf{E}}'\mathbf{H}\hat{\mathbf{E}}\mathbf{a} + whC_2}\right) \quad \text{subject to} \quad \mathbf{\Sigma}\mathbf{x} = \mathbf{y}, \frac{1}{wh}\mathbf{1}'\mathbf{x} = \rho, \boldsymbol{\mu}_{\hat{\mathbf{E}}}'\mathbf{a} = \omega. \tag{10}$$

Therefore, the overall problem is to find the highest SSIM index by searching over range of ρ and ω. Furthermore, Eq. (10) is converted into a quasi-convex optimization problem as follows:

$$\begin{aligned} &\max_{\mathbf{x}, \mathbf{a}} \left(\frac{2\mathbf{x}'\mathbf{H}\hat{\mathbf{E}}\mathbf{a} + whC_2}{\mathbf{x}'\mathbf{H}\mathbf{x} + \mathbf{a}'\hat{\mathbf{E}}'\mathbf{H}\hat{\mathbf{E}}\mathbf{a} + whC_2}\right) \\ &\qquad \text{subject to} \quad \mathbf{\Sigma}\mathbf{x} = \mathbf{y}, \frac{1}{wh}\mathbf{1}'\mathbf{x} = \rho, \boldsymbol{\mu}_{\hat{\mathbf{E}}}'\mathbf{a} = \omega, \\ &\Leftrightarrow \\ &\min : \tau \\ &\text{subject to} \begin{bmatrix} \max : \left(\frac{2\mathbf{x}'\mathbf{H}\hat{\mathbf{E}}\mathbf{a} + whC_2}{\mathbf{x}'\mathbf{H}\mathbf{x} + \mathbf{a}'\hat{\mathbf{E}}'\mathbf{H}\hat{\mathbf{E}}\mathbf{a} + whC_2}\right) \leq \tau \\ \text{subject to} \quad \mathbf{\Sigma}\mathbf{x} = \mathbf{y}, \frac{1}{wh}\mathbf{1}'\mathbf{x} = \rho, \boldsymbol{\mu}_{\hat{\mathbf{E}}}'\mathbf{a} = \omega \end{bmatrix}, \\ &\Leftrightarrow \\ &\min : \tau \\ &\text{subject to} \\ &\begin{bmatrix} \min : [\tau(\mathbf{x}'\mathbf{H}\mathbf{x} + \mathbf{a}'\mathbf{K}_1\mathbf{a} + whC_2) - (\mathbf{x}'\mathbf{K}_2\mathbf{a} + whC_2)] \geq 0 \\ \text{subject to} \quad \mathbf{\Sigma}\mathbf{x} = \mathbf{y}, \frac{1}{wh}\mathbf{1}'\mathbf{x} = \rho, \boldsymbol{\mu}_{\hat{\mathbf{E}}}'\mathbf{a} = \omega \end{bmatrix}, \end{aligned} \tag{11}$$

where

$$\mathbf{K}_1 = \hat{\mathbf{E}}'\mathbf{H}\hat{\mathbf{E}}, \tag{12}$$

$$\mathbf{K}_2 = 2\mathbf{H}\hat{\mathbf{E}}. \tag{13}$$

In Eq. (11), τ becomes a true upper bound if

$$\begin{bmatrix} \max_{\mathbf{x},\mathbf{a}} \tau\left(\mathbf{x}'\mathbf{H}\mathbf{x} + \mathbf{a}'\mathbf{K}_1\mathbf{a} + whC_2\right) - \left(\mathbf{x}'\mathbf{K}_2\mathbf{a} + whC_2\right) \geq 0 \\ \text{subject to} \quad \mathbf{\Sigma}\mathbf{x} = \mathbf{y}, \frac{1}{wh}\mathbf{1}'\mathbf{x} = \rho, \boldsymbol{\mu}_{\hat{\mathbf{E}}}{}'\mathbf{a} = \omega \end{bmatrix} \tag{14}$$

has a non-negative value. The proposed method adopts the Lagrange multiplier approach as follows:

$$\begin{aligned} L \;=\; & \tau\left(\mathbf{x}'\mathbf{H}\mathbf{x} + \mathbf{a}'\mathbf{K}_1\mathbf{a} + whC_2\right) - \left(\mathbf{x}'\mathbf{K}_2\mathbf{a} + whC_2\right) \\ & + \sum_{k=1}^{N_{\bar{\Omega}}} \lambda_k\left(\mathbf{v}_k{}'\mathbf{x} - y_k\right) + \eta_1\left(\frac{1}{wh}\mathbf{1}'\mathbf{x} - \rho\right) + \eta_2\left(\boldsymbol{\mu}_{\hat{\mathbf{E}}}{}'\mathbf{a} - \omega\right), \end{aligned} \tag{15}$$

where $\mathbf{v}_k$ $(k = 1, 2, \cdots, N_{\bar{\Omega}})$ is a vector satisfying

$$\mathbf{\Sigma} = \left[\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_{N_{\bar{\Omega}}}\right]', \tag{16}$$

and y_k $(k = 1, 2, \cdots, N_{\bar{\Omega}})$ satisfies

$$\mathbf{y} = \left[y_1, y_2, \cdots, y_{N_{\bar{\Omega}}}\right]'. \tag{17}$$

In Eq. (15), the optimal solutions satisfy $\nabla_{\mathbf{x}} L = \mathbf{0}_{wh}$, $\nabla_{\mathbf{a}} L = \mathbf{0}_M$, $\nabla_{\lambda_k} L = 0$ $(k = 1, 2, \cdots, N_{\bar{\Omega}})$, $\nabla_{\eta_1} L = 0$, $\nabla_{\eta_2} L = 0$, and the following equations are obtained:

$$2\tau\mathbf{H}\mathbf{x} - \mathbf{K}_2\mathbf{a} + \sum_{k=1}^{N_{\bar{\Omega}}} \lambda_k\mathbf{v}_k + \frac{\eta_1}{wh}\mathbf{1} = \mathbf{0}_{wh}, \tag{18}$$

$$-\mathbf{K}_2{}'\mathbf{x} + 2\tau\mathbf{K}_1\mathbf{a} + \eta_2\boldsymbol{\mu}_{\hat{\mathbf{E}}} = \mathbf{0}_M, \tag{19}$$

$$\mathbf{v}_k{}'\mathbf{x} = y_k \qquad (k = 1, 2, \cdots, N_{\bar{\Omega}}), \tag{20}$$

$$\frac{1}{wh}\mathbf{1}'\mathbf{x} = \rho, \tag{21}$$

$$\boldsymbol{\mu}_{\hat{\mathbf{E}}}{}'\mathbf{a} = \omega, \tag{22}$$

where Eq. (20) is equivalent to the constraint $\mathbf{\Sigma}\mathbf{x} = \mathbf{y}$ in Eq. (6). From Eqs. (18)–(22), the following problem can be obtained:

$$\begin{bmatrix} 2\tau\mathbf{H} & -\mathbf{K}_2 & \mathbf{\Sigma}' & \frac{1}{wh}\mathbf{1} & \mathbf{0}_{wh} \\ -\mathbf{K}_2{}' & 2\tau\mathbf{K}_1 & \mathbf{O}_{M\times N_{\bar{\Omega}}} & \mathbf{0}_M & \boldsymbol{\mu}_{\hat{\mathbf{E}}} \\ \mathbf{\Sigma} & \mathbf{O}_{N_{\bar{\Omega}}\times M} & \mathbf{O}_{N_{\bar{\Omega}}\times N_{\bar{\Omega}}} & \mathbf{0}_{N_{\bar{\Omega}}} & \mathbf{0}_{N_{\bar{\Omega}}} \\ \frac{1}{wh}\mathbf{1}' & \mathbf{0}_M{}' & \mathbf{0}_{N_{\bar{\Omega}}}{}' & 0 & 0 \\ \mathbf{0}_{wh}{}' & \boldsymbol{\mu}_{\hat{\mathbf{E}}}{}' & \mathbf{0}_{N_{\bar{\Omega}}}{}' & 0 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{a} \\ \boldsymbol{\lambda} \\ \eta_1 \\ \eta_2 \end{bmatrix} = \begin{bmatrix} \mathbf{0}_{wh} \\ \mathbf{0}_M \\ \mathbf{y} \\ \rho \\ \omega \end{bmatrix}, \tag{23}$$

where $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \cdots, \lambda_{N_{\bar{\Omega}}}]'$. Furthermore, $\mathbf{O}_{height\times width}$ and $\mathbf{0}_{height}$ are respectively the zero matrix and the zero vector, and the subscript (*height* and *width*) represents their size. Then, by solving the above problem, the proposed method can calculate the optimal vectors $\hat{\mathbf{a}}$ and $\hat{\mathbf{x}}$. Note that τ can be obtained by using the standard bisection procedures. Finally, from the obtained result $\hat{\mathbf{x}}$, the proposed method outputs the estimated intensities in the missing area Ω.

As shown in the above procedures, we can reconstruct the missing area Ω within the target patch f. Therefore, the proposed method clips patches including missing areas and performs their reconstruction to estimate all missing intensities. Specifically, we clip patches in a raster scanning order from the upper-left of the target image, and the missing areas are reconstructed if the target patches contain missing intensities. If the clipping interval is smaller than the size of the patches, multiple estimation results are obtained. In such cases, the proposed method outputs the results maximizing Eq. (6) as the final results.

4. EXPERIMENTAL RESULTS

In this section, we verify the performance of the proposed method by some experiments. Figure 1(a) is a test texture image (480×360 pixels, 24-bit color levels) that includes text regions. Figure 1(b) shows the results of reconstruction by the proposed method. For comparison, we performed the reconstruction using the conventional MSE-based methods [1]–[4], and Fig. 1(c) shows the results obtained based on the method proposed by Xu et al. [4]. We only show the results of [4] which is the sate-of-the-art one in these conventional methods due to the limitation of pages[1]. Furthermore, we show the zoomed portions around the lower-right part of the images in Figs. 1 (d)–(f). From the obtained results, it can be seen that the proposed method has achieved noticeable improvements compared to the conventional method. Different experimental results are shown in Figs. 2 and 3. Similar to Fig. 1, we can see that the proposed method can reconstruct various kinds of textures more successfully than the conventional one. Furthermore, the proposed method averagely achieves 0.0162, 0.0244, 0.0221, and 0.0036 improvements of the SSIM index over the conventional methods [1]–[4], respectively. Therefore, high performance of the proposed method was verified by the experiments.

The conventional methods generally use subspaces based on the MSE criterion. As described above, the MSE optimal algorithms do not necessarily produce images of high visual quality, and the reconstruction results tend to suffer from some degradations such as blurring. On the other hand, the proposed method adopts the SSIM index for obtaining the subspace to reconstruct missing textures. Since the SSIM index outperforms the MSE as a perceptual distortion measure, more successful reconstruction by our method is realized.

5. CONCLUSIONS

In this paper, we have presented a perceptually optimized subspace estimation method for reconstructing missing textures. The proposed method generates the optimal subspace from known patches within the target image based on the SSIM index. Furthermore, from the obtained subspace, the new algorithm, which maximizes the SSIM index by converting its problem into a quasi convex one, enables the reconstruction of missing textures. Consequently, impressive improvement of the proposed method over the previously reported methods can be confirmed.

6. REFERENCES

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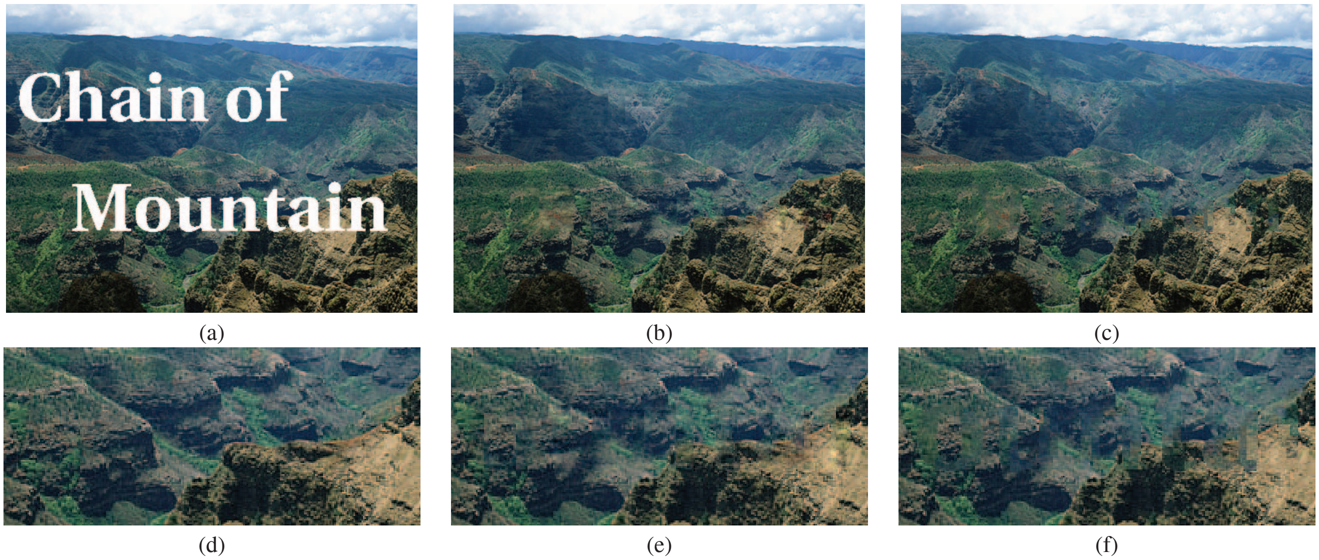

Fig. 1. (a) Corrupted image including text regions (480 × 360 pixels, 8.9 % loss), (b) Reconstructed image by the proposed method (SSIM = 0.9611), (c) Reconstructed image by the conventional method [4] (SSIM = 0.9579), (d) Zoomed portion of the original image, (e) Zoomed portion of (b), (f) Zoomed portion of (c).

(a) (b) (c)

Fig. 2. (a) Corrupted image including text regions (480 × 360 pixels, 11.3 % loss), (b) Reconstructed image by the proposed method (SSIM = 0.9219), (c) Reconstructed image by the conventional method [4] (SSIM = 0.9196).

(a) (b) (c)

Fig. 3. (a) Corrupted image including text regions (480 × 360 pixels, 11.9 % loss), (b) Reconstructed image by the proposed method (SSIM = 0.9399), (c) Reconstructed image by the conventional method [4] (SSIM = 0.9345).

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