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Adaptive missing texture reconstruction method based on kernel cross-modal factor analysis with a new evaluation criterion

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ABSTRACT

This paper presents an adaptive missing texture reconstruction method based on kernel cross-modal factor analysis (KCFA) with a new evaluation criterion. The proposed method estimates the latent relationship between two areas, which correspond to a missing area and its neighboring area, respectively, from known parts within the target image and realizes reconstruction of the missing textures. In order to obtain this relationship, KCFA is applied to each cluster containing similar known textures, and the optimal cluster is used for reconstructing each target missing area. Specifically, a new criterion obtained by monitoring errors caused in the latent space enables selection of the optimal cluster. Then each missing texture is adaptively estimated by the optimal cluster's latent relationship, which enables accurate reconstruction of similar textures. In our method, the above criterion is also used for estimating patch priority, which determines the reconstruction order of missing areas within the target image. Since patches, whose textures are accurately modeled by our KCFA-based method, can be selected by using the new criterion, it becomes feasible to perform successful reconstruction of the missing areas. Experimental results show improvements of our KCFA-based reconstruction method over previously reported methods.

1. Introduction

Missing area reconstruction has been intensively studied in the field of image processing since it can afford a number of fundamental applications. Many methods that focus on the reconstruction of important visual features such as structures and textures within target images have been proposed. Most of the methods are broadly classified into two categories: missing structure reconstruction [1–9] and missing texture reconstruction [10–22]. In addition, there have been proposed reconstruction methods which adopt the combination use of the structure and texture reconstruction approaches [23]. The variational image inpainting methods which can successfully reconstruct structure components in images have been intensively studied in this research field. The variational image inpainting is performed based on the continuity of the geometrical structure of images. Most variational inpainting methods solve partial differential equations (PDEs). One of the pioneering works was proposed by Masnou and Morel [1]. Furthermore, Bertalmio et al. proposed a representative image inpainting technique which is based on PDEs [2], and they have also realized several important achievements [3,4]. In recent years, many improvement methods of the variational image inpainting have been reported [7–9]. Although these variational image inpainting methods enable successful reconstruction of the

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structure components, images also include other different components, i.e., texture components, and alternative methods tend to output better results. The remainder of this paper focuses on the reconstruction of textures with discussion of its details.

It is well known that missing texture reconstruction is realized by several approaches such as exemplar-based methods [10–13] and multivariate analysis-based methods [14–22]. A method based on texture synthesis was first proposed by Efros and Leung [10]. Based on their idea, an exemplar-based image inpainting method was proposed by Criminisi et al. [11,12], and it became a representative method in this field. Recently, the exemplar-based approach has been improved by many researchers, and several state-of-the-art methods have also been proposed [13,22]. Generally, the performance of exemplar-based methods tends to depend on the number of training examples. A sufficient number of training examples are necessary to accurately represent texture features within target images. Thus, if sufficient training examples cannot be provided, it becomes difficult to model the relationship between missing areas and other known areas in those methods.

Missing texture reconstruction methods using multivariate analysis have traditionally been proposed, and they are based on texture approximation using various methods such as principal component analysis (PCA), kernel PCA (KPCA) [14–17] and sparse representation. Several reconstruction methods based on sparse representation have recently been proposed [18–21], and a representative one was proposed by Mairal et al. [18]. Furthermore, sparse representation can be combined with the exemplar-based approach [22]. Since the conventional methods based on multivariate analysis represent textures by using their subspaces, more successful approximation can be expected compared to exemplar-based methods. However, it should be noted that those methods generally assume that arbitrary local textures within the target image are similar to each other; that is, the target image contains almost one type of texture. Thus, if the target image consists of various textures, the missing textures should be adaptively reconstructed from only the same kinds of textures.

In this paper, we present a novel missing texture reconstruction method based on kernel cross-modal factor analysis (KCFA) [24,25]. The main contributions of our method are threefold. First, the proposed method estimates the latent relationship between two areas, which respectively correspond to missing areas and their neighboring areas, from other known parts within the target image by using KCFA. Then this approach enables reconstruction of the missing areas based on the obtained KCFA-based relationship. Second, the proposed method performs clustering of known textures based on KCFA to realize reconstruction of missing areas by using optimal clusters. In this approach, a new criterion, which is obtained from errors caused in the KCFA-based latent space, is adopted to perform the clustering and select the optimal cluster for the target missing areas. Therefore, by monitoring this criterion, the reconstruction results by the optimal clusters can be adaptively obtained as the final results. Third, the proposed method introduces a new priority estimation scheme based on the above criterion. The determination of the order for reconstructing missing areas, i.e., "priority estimation", is an important problem. By using the derived priority, missing areas, which can be successfully reconstructed by our KCFA-based method, are adaptively selected from the target image. Consequently, successful reconstruction of the missing textures can be expected by using the proposed method. It should be noted that the proposed method shown in this paper is an improved version of [26]. The biggest difference between these two methods is the use of the clustering scheme. In the proposed method, we newly perform the clustering of known textures and the selection of the best matched cluster for the target missing areas, which are realized by monitoring the new evaluation criterion, in the KCFA-based reconstruction. Therefore, the proposed method is implemented in such a way that images including several kinds of textures can be reconstructed successfully.

This paper is organized as follows. First, in Section 2, we explain the concept of KCFA and its specific procedures. Next, a new missing texture reconstruction method based on KCFA is presented in Section 3. Section 4 shows experimental results in order to verify the performance of our method. Finally, concluding remarks are presented in Section 5.

2. Kernel cross-modal factor analysis

In this section, we present an overview of KCFA [25] as a preliminary. Suppose that there is a pair of variables $\mathbf{x}_i \in \mathbf{R}^{n_x}$ and $\mathbf{y}_i \in \mathbf{R}^{n_y}$ ($i=1, 2, \ldots, N$; N being the number of samples), KCFA tries to find two linear transformations that minimize the distance between two projections in the feature space.

First, $\mathbf{x}_i$ and $\mathbf{y}_i$ are respectively mapped into the feature space via nonlinear maps $\phi_\mathbf{x}$ and $\phi_\mathbf{y}$ [27] to obtain $\phi_\mathbf{x}(\mathbf{x}_i) \in \mathbf{R}^{\tilde{n}_x}$ and $\phi_\mathbf{y}(\mathbf{y}_i) \in \mathbf{R}^{\tilde{n}_y}$. Then given $\Xi_\mathbf{x} = [\phi_\mathbf{x}(\mathbf{x}_1), \phi_\mathbf{x}(\mathbf{x}_2), \ldots, \phi_\mathbf{x}(\mathbf{x}_N)]$ and $\Xi_\mathbf{y} = [\phi_\mathbf{y}(\mathbf{y}_1), \phi_\mathbf{y}(\mathbf{y}_2), \ldots, \phi_\mathbf{y}(\mathbf{y}_N)]$, KCFA estimates two orthonormal matrices $\hat{\mathbf{U}} \in \mathbf{R}^{\tilde{n}_x \times d}$ and $\hat{\mathbf{V}} \in \mathbf{R}^{\tilde{n}_y \times d}$ as follows:

$$\{\hat{\mathbf{U}}, \hat{\mathbf{V}}\} = \min_{\mathbf{U},\mathbf{V}} \|\mathbf{U}'\Xi_\mathbf{x}\mathbf{H} - \mathbf{V}'\Xi_\mathbf{y}\mathbf{H}\|_F^2, \tag{1}$$

where $\|\cdot\|_F$ represents the Frobenius norm. The matrix $\mathbf{H}$ is an $N \times N$ centering matrix satisfying $\mathbf{H}' = \mathbf{H}$ and $\mathbf{H}^2 = \mathbf{H}$ and defined as follows:

$$\mathbf{H} = \mathbf{I} - \frac{1}{N}\mathbf{1}\mathbf{1}', \tag{2}$$

where $\mathbf{I}$ is the $N \times N$ identity matrix, and $\mathbf{1} = [1, 1, \ldots, 1]'$ is an $N \times 1$ vector. In this paper, vector/matrix transpose is denoted by the superscript $'$.

Note that in the above equation

$$\begin{aligned}\|\mathbf{U}'\Xi_\mathbf{x}\mathbf{H} - \mathbf{V}'\Xi_\mathbf{y}\mathbf{H}\|_F^2 &= \|\mathbf{H}\Xi_\mathbf{x}'\mathbf{U} - \mathbf{H}\Xi_\mathbf{y}'\mathbf{V}\|_F^2 \\ &= \mathrm{tr}(\mathbf{H}\Xi_\mathbf{x}'\Xi_\mathbf{x}\mathbf{H}) + \mathrm{tr}(\mathbf{H}\Xi_\mathbf{y}'\Xi_\mathbf{y}\mathbf{H}) \\ &\quad - 2\mathrm{tr}(\mathbf{H}\Xi_\mathbf{x}'\mathbf{U}\mathbf{V}'\Xi_\mathbf{y}\mathbf{H}).\end{aligned} \tag{3}$$

is satisfied, where $\mathrm{tr}(\cdot)$ represents the trace of a matrix. It should be noted that $\mathrm{tr}(\mathbf{H}\Xi_\mathbf{x}'\Xi_\mathbf{x}\mathbf{H})$ and $\mathrm{tr}(\mathbf{H}\Xi_\mathbf{y}'\Xi_\mathbf{y}\mathbf{H})$ are