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MF-LRTC: Multi-filters guided low-rank tensor coding for image restoration

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ABSTRACT

Image prior information is a determinative factor to tackling with the ill-posed problem. In this paper, we present multi-filters guided low-rank tensor coding (MF-LRTC) model for image restoration. The appeal of constructing a low-rank tensor is obvious in many cases for data that naturally comes from different scales and directions. The MF-LRTC takes advantages of the low-rank tensor coding to capture the sparse convolutional features generated by multi-filters representation. Using such a low-rank tensor coding would reduce the redundancy between feature vectors at neighboring locations and improve the efficiency of the overall sparse representation. In this work, we are committed to achieving this goal by convoluting the target image with Filed-of-Experts (FoE) filters to formulate multi-feature images. Then similarity-grouped cube set extracted from the multi-features images is regarded as a low-rank tensor. The resulting non-convex model is addressed by an efficient ADMM technique. The potential effectiveness of this tensor construction strategy is demonstrated in image restoration including image deblurring and compressed sensing (CS) applications.

1. Introduction

MULTI-VIEW representations of images have become a standard tool in image analysis. Such representations offer a number of advantages over one-view or image domain-based methods. Since they represent distinct but complementary information that exists at various scales, they have great potential for improving performance in compressive sensing (CS), image super-resolution and deblurring, etc. [1–10].

Due to the successful modeling of images by nonlocal and self-similarity properties, image patch-based approaches have attracted lots of attentions in past few years [11–17]. For instance, Manjón et al. [11] used a data-adaptive patch-based reconstruction model that combination with a subsampling coherence constraint to recover some of high frequency information. Unfortunately, it is well known that partial representation of patches only allows finding neighbors in a specific type of feature space, and image patches do not strictly follow the similar structure at different scale/resolution spaces. As stated in Ref. [3], in many real-world scenarios, each object can be described by multiple sets of features, where each feature describes a view of the same set of underlying objects. Specifically, for a patch in image processing community, each feature that summarizing the image patch (e.g., convoluted by a kernel) can be considered as a view of the patch. How to find multi-view representation that describes the patch character heterogeneously and integrates them into a unified representation for subsequent processing is a promising research direction. Therefore, a redundancy and complemental multi-view representation of patches will be more beneficial to reveal the underlying visual manifold.

1.1. Multi-view features

Multi-view features have ignited much interest in the image processing community, due to the flexibility of convolution operator. In the compressed sensing magnetic resonance imaging (MRI) application, Liu et al. [16] learned the dictionary in the gradient features and applied it to reconstruct the MR image. Peng and Liang [4] proposed a MR image reconstruction method with convolutional characteristic constraints. In the super-resolution application, Hong et al. [5] employed the first-order and second-order gradients as the low-resolution features. He et al. [18] introduced a Bayesian joint dictionary learning strategy for coupled feature spaces, where the first-order and second-order gradients are utilized as low-res feature space. In Ref. [7], Yang et al. defined multi-features of image patches and their spatial neighbors

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are jointly sparsely coded, via a tensor-simultaneous orthogonal matching pursuit algorithm. Utilizing the feature representation for image smoothing and deblurring also attracts some attentions. In Ref. [8], Tappen et al. learned the weight error sum of the feature maps in a discriminative fashion by end-to-end training for image denoising. Badri and Yahia [9] proposed an approach that consists in a sparse gradient data-fitting term to handle outliers together with a gradient-domain non-local low-rank prior. They employed the low-rank prior to ensure similarity between non-local gradient patches, which helps recovering high-quality clean patches from severe outlier's corruption. Zhan et al. [10] introduced a fast-orthogonal dictionary learning method into a sparse reconstruction model with the multi-class dictionaries. Due to a multidimensional dataset in dynamic MRI is treated as a series of two-dimensional matrices, Yu et al. [14] proposed a concept of tensor sparsity for the application of CS in dynamic MRI and presented the (HOSVD) as a practical example to exploit the correlations within spatial and temporal dimensions. In Ref. [19], Cho and Lee used the data-fidelity constraint in the zeroth, first and second order derivations for reducing ringing artifacts during the deblurring process. Ren et al. [20] introduced an enhanced prior for image deblurring by combining the low-rank prior of similar patches from both blurry images and its gradient map. They employed a weighted nuclear norm minimization method to enhance the effectiveness of low-rank prior for image deblurring, by training the dominant edges and eliminating fine texture and slight edges in intermediate images. Hong et al. proposed an approach which adopts multi-view locality-sensitive sparse coding in the retrieving process to recover 3-D human poses from silhouettes [21] and combined different types of features by using multi-view to achieve multiple feature fusion by unified representations hidden in hypergraph manifold hypergraph LRR learning [22]. Furthermore, Hong et.al modeled image features with a regularization term for SVM to propose a 3D object recognizing method based on multi-view data fusion [23]. All these algorithms utilize the characteristics of multi-view features to enhance the performance of image applications.

1.2. Low-rank tensor coding

Low-rank matrix approximation has been successfully applied to numerous vision problems in recent years. Several existing works have indicated that there are many repetitive image structures (or self-similarity) in an image, especially in a local region [24]. As pointed out by Refs. [15,25], an advanced sparse representation method which considers local spatial property, can be approximated by low-rank approach. However, two-dimensional low-rank model cannot fully exploit the correlation in multidimensional data sets such as multispectral data. As a more general tool to describe the high-dimensional data, low-rank tensor has gained more and more attentions [26–35]. Building on recent studies about matrix completion using the matrix trace norm, Liu et al. [26] developed three low-rank tensor completion (LRTC) algorithms to solve the tensor completion of convex optimization. Kressner et al. [27] proposed an algorithm that performs Riemannian optimization techniques on the manifold of tensors of fixed multilinear rank. Chen et al. [28] combined a rank minimization technique with Tucker model decomposition for simultaneous tensor decomposition and completion (STDC). They used factor priors to characterize the underlying joint-manifold drawn from the model factors. Narita et al. [29] used the relationships among data as auxiliary information in addition to the low-rank assumption to improve the quality of tensor decomposition. Teng et al. [30] combined the total variation regularization and low-rank matrix factorization to recover a tensor with missing data. He et al. [31] represented high dimensional images as partially separable-based low-rank tensor and employed this mathematical structure for image reconstruction from under-sampled data. Liu et al. [32] proposed the low-rank representation (LRR) to recover the lowest-rank representation of a set of data vectors in a joint way to recover the lowest-rank representation of matrix data. Ying et al. [33] formulated the problem that recovering N-dimensional exponential signals from partial observations as a low-rank tensor completion problem with exponential factors and demonstrated the full signal can be reconstructed by simultaneously exploiting the tensor decomposition and the exponential structure of the associated factors. Refs. [34,35] gave a literature overview of current developments in low-rank tensor approximation, with an emphasis on function-related tensors.

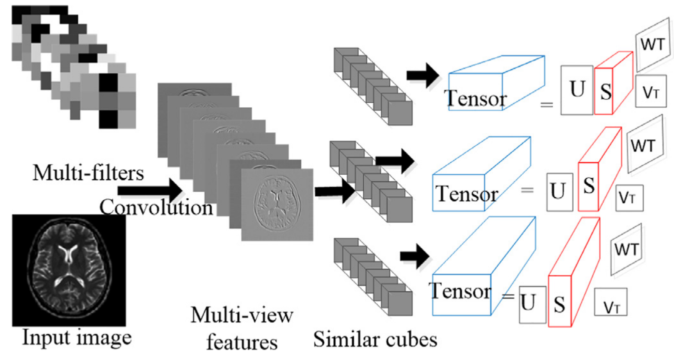

Fig. 1. Exploration of multi-filters guided low-rank tensor coding for image restoration.

Instead of the above local approaches that viewed the whole data as a low-rank tensor, some researchers considered some clustered elements in the whole data as a low-rank tensor, via the nonlocal strategy. For denoising purpose, Rajwade et al. [36] proposed to group together similar patches from a noisy image into a 3D stack and manipulate the higher-order singular value decomposition (HOSVD) coefficients of this stack by hard thresholding to produce the final filtered image. Peng et al. [37] proposed an effective multispectral images denoising approach by combinatorically considering the nonlocal similarity over space and the global correlation across spectrum intrinsic characteristics underlying an multispectral images. Dong et al. [38] grouped similar 3D image patches into 3rd tensors, which lend themselves to be approximated by low-rank tensors to fully exploit the spatial-temporal dependency. Zhang et al. [39] modeled nonlocal similar patches through the multi-linear approach and proposed two tensor based methods for image denoising. They proposed two adaptive tensor nuclear norms by exploiting low-rank prior in tensor presentation of similar patches. For the general reconstruction purpose, Yu et al. [40] proposed a concept of tensor sparsity for the application of CS in dynamic MRI, and presented the HOSVD as a practical example. Tan et al. [41] trained a tensor-based spatial-temporal dictionary for sparse representation of an image sequence during reconstruction process. They considered the correlations among atoms and across phases to capture the characteristic of an object.

1.3. Motivation and contributions

The investigation of multi-view features to facilitate image restoration has appealed to many researchers. Generally, the complementary information of distinct characteristics is exploited to reveal different physical meanings and statistical properties of patches; hence a better manifold structure is utilized. In this paper, we further go ahead to exploit the high-dimensional property of the multi-features by low-rank tensor formulation and apply it to image deblurring and CS recovery. Fig. 1 shows the exploration of the proposed algorithm. The proposed algorithm exploits