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A robust bi-sparsity model with non-local regularization for mixed noise reduction

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ABSTRACT

Sparse representation model (SRM) has been widely used in many image processing and computer vision tasks. However, the conventional SRM usually neglects the prior knowledge about similar signals. Considering the fact that similar signals also have subtle differences, in this paper we propose a robust bi-sparsity model (RBSM) to effectively exploit the prior knowledge about the similarities and the distinctions of signals. In RBSM, similar signals are encouraged to be coded on the same sub-dictionary. But the distinctiveness of similar signals is also addressed by imposing the l_0-norm regularization on the difference between each coefficient and its non-local means. In addition, a weight vector is incorporated into the loss function to make the proposed model robust to outliers. We apply RBSM for mixed noise reduction and experimental results show that our proposed model is superior to several state-of-the-art mixed noise removal methods.

1. Introduction

Digital images are easily corrupted by noise due to the imperfect acquisition process and the possible transmission errors. In many real applications, the noise introduced into images can be modeled as white Gaussian noise (GN) and impulse noise (IN). GN is usually introduced into images due to the thermal motion in sensors [15], while IN is often introduced by faulty memory locations or bit errors [43].

In the past two decades, various techniques have been developed to suppress single noise in images, such as the methods in [8,12,29,36,47] for IN removal and the algorithms in [5,10,16,33,49] for GN reduction. Due to the totally different distributions of GN and IN, applying the single noise reduction methods directly to remove mixed noise always bring about bad results. Generally speaking, mixed noise is more difficult to be suppressed compared to one single noise. In this paper we will address the mixed noise removal problem.

For the GN corrupted image, a random value sampled from a zero-mean Gaussian distribution is added to the original intensity of each pixel. But for an image contaminated by IN, only a part of its pixels are replaced by some random values and the remaining ones are untouched. In general, there are two kinds of IN, namely, salt-and-pepper noise (SPN) and random valued impulse noise (RVIN). For SPN, the noisy pixel values are randomly chosen as the minimum or maximum of the dynamic range, while for RVIN, the noisy pixel can take any value in the range.

Since the IN corrupted pixels carry no information of the original ones, it is reasonable to abandon them and just use the remaining pixels to estimate the noise-free image. Actually, most of the mixed noise reduction methods adopted this

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"detecting then filtering" strategy. Combined with some noise detectors, the conventional mean filters may be extended to suppress the mixed noise. In [14], an image statistic *rank order absolute difference* (ROAD) is designed to describe the probability of a pixel being corrupted by IN, which is further incorporated into the bilateral filter (BF) [34] for mixed noise removal. The two phase noise detector based weighted mean filter proposed in [29] is another modification of BF. In [41], by using the statistic *robust outlyingness ratio* (ROR) to detect noise, the *non-local means* (NLM) [3] filter is also extended to remove mixed noise.

In the past few years, the sparse representation model (SRM) emerged as a powerful signal processing tool and has been widely applied in many image processing and computer vision tasks, including denoising [11,13,30,44], deblurring [31,39], super-resolution [19,23,25,45,50], inpainting [24], segmentation [21,46], and classification [1,9,18,22,38,48,51]. SRM assumes that the natural images are sparse in some domain (database or dictionary) and they can be well reconstructed by the linear combination of a few atoms from the dictionary. For image denoising applications, noisy image patches are reshaped into vectors as and served as the units of SRM. By assuming that the sparse coding residuals obey the Gaussian distribution, the SRM achieved satisfying performance in GN reduction. However, the conventional SRM fails in mixed noise removal because the sparse coding residuals of mixed noisy corrupted data no longer follow the Gaussian distribution.

Recently, by using the detection trick, a few works extended the sparse model to suppress the mixed noise. In [40], Xiao et al. employed the adaptive median filter (AMF) [17] and the adaptive center-weighted median (ACWM) filter [7] based detectors to identify the SPN and the RVIN, respectively. The noisy pixels were then excluded and only the clean ones were used for sparse coding. Later, Liu et al. [27] presented a complex weighted sparse model for mixed noise reduction, where the noise detection is achieved by solving an optimization problem.

One common limitation of these SRM based mixed noise removal methods is that the image patches are processed individually, ignoring the correlations among similar patches. The self similarity prior suggests that natural images are rich in similar local structures and its use helps to improve the qualities of results [4]. Recent works have combined the self-similarity with the SRM to remove GN [11]. However, there exist few works that exploit both the self-similarity and the sparsity priors for mixed noise reduction despite of their great capacities in removing noise and preserving the texture information. In [20], a weighted encoding with sparse nonlocal regularization (WESNR) model was proposed to suppress mixed noise. In that method, the similar patches were expected to share similar coding coefficients by forcing the coefficient of each exemplar patch close to the mean coefficient of the non-local similar patches. The WESNR gained the state-of-the-art mixed noise removal performance owing to the priors of sparsity and nonlocal similarity it used. However, the constraint that the coding coefficients of similar exemplar patches are close to their average is too strict, which neglects the fact that the similar patches share similarities but also have differences.

To address the concerns above, in this paper we propose a robust bi-sparsity model (RBSM) to remove mixed noise in images. In the RBSM, the similar patches are assumed but not limited to lie in a subspace. More specifically, the difference between the coefficient of each exemplar patch and the non-local means is regularized by the l_0-norm. By doing this, we encourage similar patches to be coded by the same sub-dictionary. But we do not strictly confine the similar patches to the same subspace because the l_0-norm permits small difference existing in the sub-dictionaries of similar signals. As a result, our model subtly depicts the fact that similar patches share some similarities but also have noticeable differences to keep their distinctions.

2. The proposed model

For convenience, throughout the paper we denote images by boldface capital letters, e.g., $\mathbf{X}$. We denote patch matrices by capital letters, e.g., X (when used as superscript or subscript they denote scalars). The patch matrix's columns are the vectorized image patches that are denoted by boldface lowercase letters, e.g., $\mathbf{x}$. The lowercase letters, e.g., x, are used to denote the scalars (pixels).

2.1. RBSM

When an image corrupted by IN, just a part of pixel values are changed and the remaining ones are still the same. Inspired by this, a number of IN reduction methods [32,40] adopted some noise detectors to identify the IN corrupted pixels, then the unaffected clear pixels were used to fix the corrupted ones. Analogously, for mixed GN and IN corrupted images, one can also first identify the IN, then use some methods to filter out the noise. In SRM, one should exclude the noisy pixels and restrain the sparse coding on the non-IN corrupted pixels. [28],

$$\hat{\alpha} = \arg\min_{\alpha} \|\mathbf{w} \odot (\mathbf{x} - D\alpha)\|_2^2, \quad s.t. \quad \|\alpha\|_0 \le L \tag{1}$$

where $\mathbf{x}$ is the vectorized noisy image patch extracted from the noise corrupted image; $\odot$ denotes the Hadamard product (element-wise product), and $\mathbf{w}$ is a weight vector generated by some noise detectors, whose entry $0 \le w_j \le 1$ denotes the cleanliness of corresponding pixel x_j. Especially, $w_j = 0$ means x_j is a noisy pixel while $w_j = 1$ indicates that x_j is a clean one.

From Eq. (1), one can see that, thanks to the weight vector and the Hadamard product, the IN corrupted pixels were assigned with smaller weights while the others were assigned with larger weights in the SRM. In other words, the IN