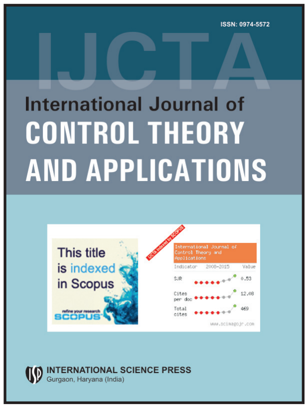

International Journal of Control Theory and Applications

ISSN : 0974-5572

© International Science Press

Volume 10 • Number 24 • 2017

Image Denoising Through Dictionary Pair Learning Model

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Abstract: This paper proposes an image denoising on dictionary pair learning algorithm. Visual information is transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image denoising involves the manipulation of the image data to produce a visually high quality image.
Keywords: Dictionary pair learning algorithm.

1. INTRODUCTION

Image denoising has been a well-studied predicament in the image processing area and continues to attract researchers with an aim to perform better re-establishment in the presence of noise. By the rise in the number of image sensors (or pixels) per unit area of a chip, modern image capturing devices be ever more sensitive to noise [1]. Camera manufacturers, then depend on image denoising algorithms to reduce the effects (Madhvi Gupta, Vivek Kumar, C. Subramani, G.K. Banerjeee, N.K. Sharma) of such noise artifacts in the resultant image. Newly proposed denoising method use different approach to deal with the problem. The best performing techniques can be shown to share a common frame in that they work by combining similar patches to affect denoising, even though the parameters of assumed framework are estimated in rather different ways. Based of DPLG, the method considers the inter-class and intra-class incoherence constraint of the mixture dictionary [2], and for the study dictionary, it should maximize the total scatter and the between-class scatter of the signal after coding, separately and then the trained incoherence dictionary is used for sparse representation. The method not only preserves the benefit of low computational complexity of DL model, but also it can discover a more discriminative dictionary and make the signal more separable after coding.

2. LITERATURE SURVEY

Image is being corrupted by noise in the form of capturing, recording and transmission [2]. The original image X is processed by adding a gaussian noise to clear image Y that is

$$X = V + Y$$

where, V is the additive white Gaussian noise with mean of zero and a standard deviation σ. Image denoising plays an important role in the field of transmission and capturing. Our aim is to restore the original clear image X from the noisy image Y, which is used to find the inverse transform of noisy image to original clear image. Moreover various denoising methods proposed the original clear image. Since the noisy image are getting exploited by various spatial correlations.

A dictionary pair learning (DPL) model is designed for various image denoising methods [3]. With the help of DPL model, the dictionary is used to define the various features of 2D image patch along with graph laplician operator lead to smoothing process. However the image patch of 2D sparse coding represents the controlled NP- hardness of the dictionary pair and the 2D sparse coding matrices of image denoising. During this process, the vectorized image patches should be clustered into K subsets by means of K-means which results in one compacted PCA sub-dictionary designed for each cluster used. According to DPL model, 2D image patches are capable of clustering into subsets through PCA sub-dictionary pairs[4]. The 2D image patches are similar to each subset in the PCA sub-dictionary to 2DPCAsub dictionary pair and use need to expand the PCA sub-dictionary to 2D PCA sub-dictionary [5] for each cluster. According to the 2D image patches sample of noisy image contains multi- resolution with sliding window [6]. During the process of one DPL model has high quality image with non-linear distribution such as clustered faces with serious computational challenge. The literature proposed a subspace indexing model on grassmann manifolds [7] has a set all linear subspaces by means of a fixed dimension with extract PCA subspace which result in leaf node. However, the large amount of effective local space is then introduce an grassmann manifolds [8] distance which is linear subspaces of SIM-GM are capable of manipulating the leaf nodes into data partition tree. The most effective of local subspace is bottom to up merging approach. Therefore, to extend the PCA subspace dictionary to 2DPCA subspace pair dictionary. Using grassmann manifolds in dictionary pair learning algorithm, results on benchmark images with Berkeley segmentation datasets shows the proposed DPLG algorithm be more comparable than state-of-the-art image denoising method as well as the internal denoising method and the external denoising method are executed.

3. PROPOSED METHOD

In the proposed method we are using external patch prior guided algorithm and three dimensional image demising model to remove demising and to improving the PSNR and SSIM values. Then proposed a three-dimensional image demising model, namely, the Dictionary Pair Learning (DPL) model, and we design a corresponding algorithm called the Dictionary Pair Learning on the Grossmann-manifold (DPLG) with External patch prior guided algorithm. The DPLG algorithm also improves the SSIM values of the perceptual visual quality for denoised images using experimental evaluations on benchmark images and Berkeley segmentation datasets. Moreover, the DPLG also produces the competitive PSNR values from popular image denoising algorithms.

Dictionary Pair Learning Algorithm

In two-dimensional structure with sparse sensing in transformation domain, we need to find two non- linear transformations simultaneously by mapping columns and rows of image patches under the sparse restriction. In DPL model, dictionary pair <A; B> and sparse coding matrices S are all unknown, and their simultaneous solution. Therefore learning strategy is to decompose the problem that provides a computational effective approach to non-linear dimensionality reduction that has locality-present properties and natural connection to clustering and also to reconstruct the denoised image Some potential applications and illustrative examples are discussed. Finally we calculate the PSNR values for each images and produce output shown in Table 1.

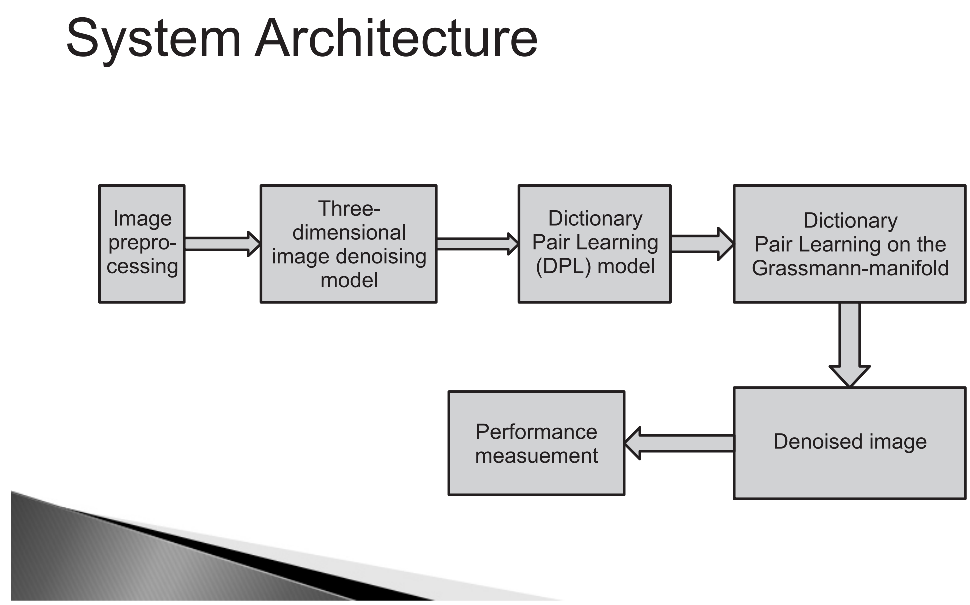

Figure 1: System architecture of DPLG

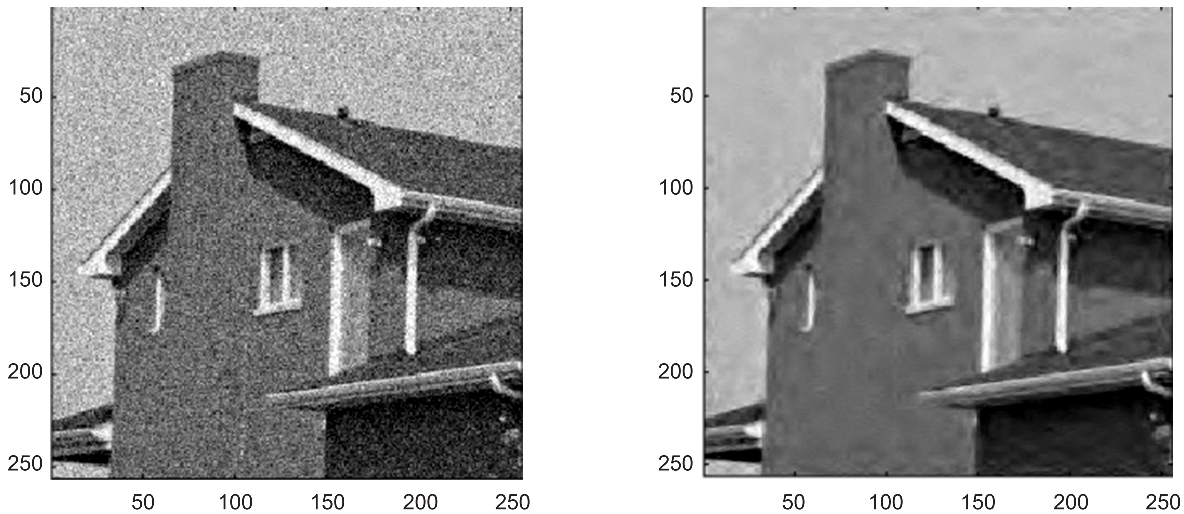

Figure 2: Noisy and denoised image

Table 1
Comparison Denoised PSNR values

Noise variance	*Test image*	*Noisy PSNR*	*Denoised PSNR*	*Denoised PSNR[9]*
20	Lena	28.16	37.42	28.50
	House	28.16	36.95	---
	Man	28.16	35.49	27.33
10	Lena	30.66	40.61	32.20
	House	30.66	40.33	---
	Man	30.66	38.92	31.33
5	Lena	40.21	44.01	36.51
	House	40.21	43.92	---
	Man	40.21	43.00	35.91

TTSP Algorithm

Step 1: Take the input image as original image.

Step 2: In this image first node is root node including the image patches

Step 3: Then split the root node as eight eigenvectors as X and Y. X as original image and Y as noisy image.

Step 4: In the root node, split the patch image as P1, P2, P3, P4.

Step 5: If we take patch P1of eigenvector, there are three rows and three columns. If there is an color inside the patches is matching then remove the color from the patch.

Step 6: In case inside the node if the X, A < partition image. Then stop the partition, ELSE repeat the step 2.

Step 7: Then collect the sub-dictionary as X and Y

DPLG Algorithm

Step 1: Take the input as noisy image and output as denoised image.

Step 2: Extract the 2-D image patches from the original image

Step 3: Repeat the Step1-3 followed in TTSP algorithm. Divide the image A and B (A as original and B as noisy image)

Step 4: Then keep the sub-dictionary pairs as Ak and Bk and centre as C. For each 2-D patch subset follow the TTSP algorithm.

Step 5: Merge those image as sub-dictionary pairs using SM algorithm.

Step 6: Select the corresponding sub-dictionary pairs of (Ak, Bk) for each noisy image patches from the current noisy image.

Step 7: Choose the neighborhood similarity between each noisy image patches.

Step 8: Smoothing and reconstruction process will start.

Step 9: Reconstuct the denoised image from the original image and collect the image from the denoised image patches.

4. SIMULATION AND RESULTS

The two dimensional noisy image is chosen as MATLAB 6.4 version software is used for simulation. The above Table 1 shown the different values of sigma and the noisy and denoised values of PSNR. The objective of image quality metric plays an main role in image denoising applications. Image quality assessment metrics are typically used are the Peak Signal-to-Noise Ratio (PSNR) . The PSNR is the simplest most widely used image quality metrics. The high PSNR value gives the high visual perception. The denoised image has high PSNR value compared than noisy PSNR. In Figure 2 shows the corresponding noisy and denoised images.

5. CONCLUSION

We proposed a dictionary pair learning (DPL) model which learn a single synthesis dictionary, DPL learns jointly a synthesis dictionary and an analysis dictionary such a pair of dictionaries work together to perform representations. Moreover, extensive experimental results are achieved on the benchmark images. DPLG algorithm can obtain better than average performance for restoring the visual effect than the state-of-the-art internal denoising methods. In future, we would like to consider several potential problems such as learning three dimensional multiple dictionaries for video denoising and exploring the fusion of manifolds denoising and multi-dimensional sparse coding techniques. The proposed system give the additional denoised PSNR value compared than existing method.

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