Image Denoising Algorithm Based on Non Related Dictionary Learning

Yao Nan¹, Wang KaiSheng² and Cai Yue³
¹Department of Jiangsu Electric Power Company Research Institute, NanJing Jiangsu, 211107, China
²Department of Yangzhou Power Supply Company, YangZhou Jiangsu, 225000, China
³Department of Nanjing Yinshi Software Co.,Ltd., NanJing Jiangsu, 210037, China

Abstract. In allusion to the problem that it is difficult for the existing denoising algorithms to keep image details, an image denoising algorithm based on nonrelated dictionary learning is proposed in this article. Firstly, the nonrelated dictionary learning algorithm is adopted to obtain the redundant dictionary; then, ROMP algorithm is adopted to find the sparse representation coefficient of each image block in the redundant dictionary, and the sparse representation coefficient is used for image denoising. Since the nonrelated redundant dictionary can comprehensively describe the image texture and detail information, the denoising quality of the image is improved. Relevant experiment results show: compared with similar algorithms, PSNR value of the algorithm proposed in this article is superior to that of the existing advanced algorithm, and the algorithm can well keep the image detail and texture information, thus to improve visual effect.

Keywords: Dictionary Learning; Non Related; Redundant Dictionary; Sparse Encoding; Image Denoising

1 Introduction

Digital images are usually polluted by various noise sources during the acquisition or transmission process, and the existence of noises seriously influences the effectiveness and reliability of such subsequent processing as feature extraction, target detection and identification. In order to improve image quality, it is necessary to remove such noise interference in images. Therefore, denoising issue becomes a hot research issue in the fields of computer vision and image processing.

The existing image denoising algorithms can be basically divided into three types: denoising algorithm based on spatial filtering, denoising algorithm based on transform domain filtering and denoising algorithm based on learning. Specifically, the denoising algorithm based on spatial filtering involves Gaussian filtering, bilateral filtering, guide filtering, nonlocal mean filtering, etc.¹,² wherein the basic thought thereof is to adopt the local self-similarity or nonlocal self-similarity of the image for denoising, and such algorithm usually has the advantages of high computation efficiency, but the denoised
images are usually too smooth; the denoising algorithm based on transform domain filtering involves Fourier transform, wavelet transform, BM3D algorithm, etc.\textsuperscript{[3,4]}

2 Dictionary Learning Model

Firstly, we simply review the dictionary learning model: for a group of given samples \(Y=(y_1, \cdots, y_K) \in R^{m \times K}\), the purpose of dictionary learning is to obtain a redundant dictionary \(D=(d_1, d_2, \cdots, d_m) \in R^{m \times m}\) through learning so that each sample \(y_k (k=1, \cdots, K)\) can be expressed as sparse vector \(x_k (k=1, \cdots, K)\) through sparse representation. The dictionary learning problem can be expressed as follows:

\[
\begin{align*}
\min_{D, x} & \quad \|Y - DX\|_F^2 \\
\text{S.T.} & \quad \|d_i\| = 1, \quad \|x_k\|_0 \leq T_0 \quad \forall i, k
\end{align*}
\]

In the above formula, \(X=(x_1, x_2, \cdots, x_K) \in R^{m \times K}\) is coefficient matrix, and \(T_0\) denotes sparsity. The above dictionary learning problem (1) can be solved by MOD algorithm, K-SVD algorithm or online dictionary learning algorithm\textsuperscript{[14]}

3 Image Denoising Algorithm Based on Non Related Dictionary Learning

The denoising algorithm proposed in this article includes two processes: firstly, the non-related dictionary learning algorithm is adopted to obtain the redundant dictionary of which atoms have relatively strong irrelevance; then, the efficient ROMP algorithm is adopted to solve the sparse representation coefficient of each image block in the dictionary, and meanwhile such coefficient is adopted to recover the original image.

The image noise is considered as additive noise, and the observation model thereof is as follows:

\[Y = X + \nu\]

In the above formula, \(Y\) is the image polluted by noise, \(X\) is the original image, and \(\nu\) is the random noise.
4 Non related Redundant Dictionary Learning

Firstly, the noise image $Y$ is divided into $K$ mutually overlapped image blocks with the size of $\sqrt{n} \times \sqrt{n}$, and the $k$ th image block is expressed as column vector $y_k \in \mathbb{R}^n$; then, $L$ image blocks are randomly selected from $K$ image blocks as the sample set $\{p_l\} (l = 1, \cdots, L)$; then, the samples are trained to obtain the non-related redundant dictionary $D \in \mathbb{R}^{n \times m}$. The non-related dictionary learning problem is expressed as follows:

$$
\begin{align*}
\min_{D, Q} & \quad \|P - DQ\|_F^2 + \lambda \|D^T D\|_F^2 \\
\text{s.t.} & \quad \|d_i\|_0 \leq T_0, \quad \forall i, l
\end{align*}
$$

In the above formula, $P = \{p_1, p_2, \cdots, p_L\}$, $Q = \{q_1, q_2, \cdots, q_L\}$. The non-related dictionary learning algorithm is adopted to solve the optimization problem (14) to obtain the non-related redundant dictionary $D$.

5 Image Denoising

In this section, the non-related redundant dictionary $D$ obtained through learning is adopted to recover the original image. Specifically, ROMP algorithm is adopted to solve the sparse encoding problem to obtain the sparse representation coefficient which is used to recover the original image. In order to adopt image sparsity for denoising, it is necessary to obtain the sparse representation coefficient of each image block $y_k \in \mathbb{R}^n$ in the dictionary $D$. Through the non-related redundant dictionary $D$ obtained in section 3.1, the sparse encoding problem used for solving the sparse representation coefficient $a_k$ can be expressed as follows:

$$
\begin{align*}
\min_{a_k} & \quad \|y_k - Da_k\|_2^2 \\
\text{s.t.} & \quad \|a_k\|_0 \leq T_0
\end{align*}
$$

In the above formula, $D = [d_1, d_2, \cdots, d_m]$, and $d_j$ is the $j$ th column of the dictionary $D$ (or the $j$ th atom). ROMP algorithm is adopted to obtain the sparse representation coefficient $a_k$ corresponding to the $k$ th image block.

Through the non-related redundant dictionary $D$ obtained by learning and the sparse representation coefficient $a_k$, the $k$ th denoised image block $x_k = Da_k$ can be
obtained. Image block $x_k$ is jointed according to position and the overlapped parts of the image blocks are averaged to obtain the denoised integral image as follows:

$$
\hat{X} = \left( \sum_k R_k^T R_k \right)^{-1} \left( \sum_k R_k^T x_k \right)
$$

In the above formula, $R_k$ is used to extract the matrix of the $k^{th}$ image block. For example, $R_k Y$ denotes the $k^{th}$ image block of image $Y$.

6 Experiment Result Analysis

In this section, the image denoising experiment is adopted to verify the algorithm performance and compare the algorithm proposed in this article with K-SVD algorithm [6] and BM3D algorithm [3]. Experiment 1 is used to compare the denoising visual effects of different algorithms; Experiment 2 aims at presenting the influence of noise on algorithm performance and different reconstruction effects; Experiment 3 aims at presenting the influence of dictionary atom number on algorithm performance; Experiment 4 aims at presenting the influence of the overlapped pixels of the image block on algorithm performance.

In the following simulation, the gray level image with the size of $256 \times 256$ pixels is selected, and then 20,000 image blocks are randomly selected for dictionary learning, wherein the size of the image block is $8 \times 8$, the number of the overlapped pixels of the neighboring image blocks is 7 and the atom number of the dictionary $D$ is 1024, namely $D \in \mathbb{R}^{64 \times 1024}$. Specifically, PSNR (Peak Signal-to-Noise) is adopted to measure the algorithm reconstruction performance.

Experiment 1: Influence of Noise on Algorithm Performance

This experiment aims at comparing the algorithm performances under different noise mean variances, wherein the noise is Gaussian white noise. PSNR values (the first three images in Experiment 1 are selected) of three algorithms under different noise mean variances are as shown in Table 1. According to Table 1, compared with K-SVD algorithm and BM3D algorithm, the algorithm proposed in this article has higher PSNR value and stronger noise adaptability.
### Experiment 2: Influence of Overlapped Pixel Number on Algorithm Performance

This experiment aims at presenting the influence of the overlapped pixel number on algorithm performance, wherein the noise is Gaussian white noise with mean variance of $\sigma = 30$, the pixel number is from 0 to 7, and other simulation conditions are not changed. PSNR values (mean value obtained from the four images in Experiment 1) of the two algorithms under the condition of different overlapped pixel numbers are as shown in Fig. 2. According to Fig. 2, the performances of the algorithm proposed in this article and K-SVD algorithm are both improved along with the increment of the overlapped pixel number, and when the overlapped pixel number is more than or equal to 6, the performance of the algorithm proposed in this article becomes stable.

![Graph showing influence of overlapped pixel number on PSNR](image)

**Fig. 1.** Influence of Overlapped Pixel Number

### Table 1. Comparison of PSNR Values of Three Algorithms

<table>
<thead>
<tr>
<th>$\sigma$</th>
<th>barbara</th>
<th>cameraman</th>
<th>westconcordorthophoto</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>K-SVD</td>
<td>BM3D</td>
<td>Algorithm in this Article</td>
</tr>
<tr>
<td>30</td>
<td>26.4347</td>
<td>27.3498</td>
<td>28.9327</td>
</tr>
</tbody>
</table>

Copyright © 2016 SERSC
7 Conclusion

In allusion to the partial texture information loss during image denoising process, an image denoising algorithm based on non-related dictionary learning is proposed in this article. In this algorithm, the noise image is firstly divided into mutually overlapped image blocks, and a certain quantity of these image blocks are randomly selected for subsequent dictionary learning; then, non-related dictionary learning technology is adopted to obtain the redundant dictionary with relatively strong irrelevance; finally, the sparse encoding algorithm is adopted to obtain the sparse representation coefficient of each image block in the redundant dictionary, and such sparse representation coefficients are used to recover the original image. The experiment result shows: since the redundant dictionary obtained through non related dictionary learning technology can strongly represent the image texture information, PSNR (Peak Signal to Noise Ratio) of the algorithm proposed in this article is superior to that of the existing advanced algorithm, and the algorithm can well keep the image detail and texture information, thus to improve visual effect.

References

[2] Li, T., Distributed Key-Value Store on HPC and Cloud Systems. 2nd Greater Chicago Area System Research Workshop (GCASR). 2013