Novel speed up strategies for NLM Denoising With Patch Based Dictionaries
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Abstract— In this paper, a novel technique to speed-up a nonlocal means filter is proposed. In the original nonlocal means (NLM) filter most of its computational time is spent on finding distances for all the patches in the search window. Here we build a dictionary in which patches with similar photometric structures are clustered together. Dictionary is built only once with high resolution images belonging to different scenes. Since the dictionary is well organized in terms of indexing its entries, it is used to search similar patches very quickly for efficient NLM denoising. We achieve a substantial reduction in computational cost compared to original NLM method especially when the search window of NLM is large, without much affecting the PSNR. Secondly, we show that by building a dictionary for edge patches as opposed to intensity patches it is possible to reduce the dictionary size; thus further improving the computational speed and memory requirement. The proposed method preclassifies similar patches with the same distance measure as used by NLM method. The proposed algorithm is shown to outperform other prefiltering based fast NLM algorithms computationally as well as qualitatively.

Keywords: - NonLocalMeans, Clustering, Denoising, edge patch,

I. INTRODUCTION

IN RECENT years, images and videos have become integral parts of our lives. Applications now range from the casual documentation of events and visual communication to the more serious surveillance and medical fields. This has led to an ever-increasing demand for accurate and visually pleasing images. However, images captured by modern cameras are invariably corrupted by noise. With increasing pixel resolution but more or less the same aperture size, noise suppression has become more relevant. While advances in optics and hardware try to mitigate such undesirable effects, software-based denoising approaches are more popular as they are usually device independent and widely applicable. In the last decade, many such methods have been proposed, leading to considerable improvements in denoising performance. We studied the problem from an estimation theory perspective to quantify the fundamental limits of denoising. The insights gained from that study are applied to develop a theoretically sound denoising method in this paper.

II. BACKGROUND

2.1 ADDITIVE WHITE GAUSSIAN NOISE

White noise is a random signal with a constant power spectral density. Gaussian noise is statistical noise having normal distribution. The probability density function (PDF) of a white Gaussian noise is given by

\[
PDF(z) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(z-\mu)^2}{2\sigma^2}}
\]

where, \( z \) represents the Gaussian random variable, \( \mu \) is the mean of \( z \) and \( \sigma \) is the standard deviation of \( z \). Figure 2-1 shows the probability density function for Gaussian noise.

2.2 Image Denoising Domains

Image denoising can be performed either in the frequency domain or in the spatial domain. In case of frequency domain, an image is transformed into the frequency domain, the denoising operations are performed there, and the resulting denoised images are transformed back into the spatial domain.

![Probability Distribution for Gaussian noise](image.png)

2.3 Non-Local Means algorithm

In the Non-Local Means algorithm, a discrete noisy image \( v = \{ v(j) | j \in I \} \), where \( I \) is the input image, can be denoised by the estimated value \( \text{NLM}(v(i)) \) for a pixel \( i \). It is compute as a weighted average for all of the pixels in
the image,

\[ NL[v][i] = \sum_{j} w(i, j)v(j) \]

The weight \( w(i, j) \) is computed as,

\[ w(i, j) = \frac{1}{Z(i)} e^{-\frac{[v(N_i) - v(N_j)]^2}{\sigma^2}}. \]

Here, \( Z(i) \) is a normalization constant such that,

\[ Z(i) = \sum_{j} e^{-\frac{[v(N_i) - v(N_j)]^2}{\sigma^2}}. \]

Figure 2-2 shows an example of the patch similarity measure for the NLM algorithm. Here, the reference patch \( p \) is compared with its neighboring patches \( q1, q2 \) and \( q3 \). \( q1 \) and \( q2 \) are more similar to the reference patch \( p \) than \( q3 \), their weights, i.e., \( w(p, q1) \), \( w(p, q2) \), will be higher than \( q3 \) weight, i.e., \( w(p, q3) \).

Figure 2-2: The Non-Local Means scheme where similar patches \( q1 \) and \( q2 \) are assigned weights larger than \( q3 \).

2.4 Non local means

The Non-Local Means algorithm has been used in many applications. It has been used in medical imaging such as on MR brain image [14][15], CT scan image [16], 3D ultrasound imaging [17][18], diagnosis of heart echo images [19]. It has been used in other applications such as video denoising [20][21], SAR image denoising and metal artifact detection.

**Improvement on non local means:**

Many improvements have been suggested on the Non-Local Means algorithm in recent years. Most of the significant improvements on the Non-Local Means algorithm have been done using the patch regression, probabilistic early termination, a patch based dictionary, neighborhood classification, principal component analysis and cluster trees. In this section, we have described them briefly.

The proposed dictionary based NLM and their improvements on edge patch based dictionary outperforms the original NLM by preselecting the similar patches and performs denoising based on the calculated weights. In addition, edge patch based dictionary reduces space and time to perform denoising by preselecting similar patches based on residual edge image.

**III. NLM THROUGH DICTIONARY BUILDING**

A. NLM Image Denoising

A nonlocal means filter replaces each pixel in the noisy image with the weighted average of all other pixels in the image. This can be represented as,

\[ NLM(u(i)) = w(N_i, N_j)u(j) \]

where \( u(i) \) is the pixel being filtered, \( u(j) \) is any other pixel in the image, \( N_i \) is the neighbourhood of \( i \)th pixel in the image and \( w(N_i, N_j) \) weight with which each noisy pixel is multiplied with. Weight function is a measure of the similarity between neighbourhoods ( \( N_i \) ) and ( \( N_j \) ) and computed by finding the Euclidean distance between them. Pixels which are near to the center of the neighbourhood should be given more weight than pixels at far and hence this distance function is further weighted by a Gaussian kernel of standard deviation \( b \). This can be represented as,

\[ NLM(u(i)) \sum_{j \in N} w(N_i, N_j)u(j) \]

B. Previous Prefiltering Based Speed-Up Strategies

According to the true NLM principle, search for similar patches should be carried out in the entire image which is still very high. Here \( s \) is half length of the search window. In [14], [15] authors preselect only a few
number of patches from the restricted search space with a
different distance measure which is not data driven.
Average gray level and variance or gradient have been
used for patch comparison. Two patches with different
textures may have same mean and gradient values.
Though these methods speed up the computation, they
are found to be inaccurate because the preselection
procedure may end up selecting patches which are
dissimilar.

C. MOTIVATION

In natural images similar patches may lie at any
location in the image, the basic premise with which the
NLM strategy works. Accordingly, we need to find
distances between all patches which is computationally
not feasible. To increase the computational efficiency,
we restrict the search space as suggested in [13] shown
with a green colored square box in Fig. 1. Here it is
noticed that many patches which are similar to the
reference patch (yellow patch at the center) lie outside
the search space. On the other hand, many dissimilar

![Illustration of existence of similar patches in different images. Contexts are very different, but patches are nearly identical.](image)

patches lie inside. Thus searching patches in the
restricted space does not always guarantee to provide a
good collection of only similar patches. Interestingly,
similar to this, in different images also we observe very
similar patches existing at different locations. Fig. 1
illuminates this with two sets of at many locations in
these images their exist identical patches shown with the
same colored square boxes. Such patches from different
images can be collected in a single dictionary where
these will be arranged in different clusters based on their
similarity. Unlike the case discussed for a limited search
space, here in any cluster we find only very similar
patches irrespective of where they are located. Further
these patches can be searched and retrieved very quickly
from the dictionary for NLM denoising.

3 Edge Patch Based Denoising

Edge preserving filters viz. bilateral or anisotropic, are
applied on noisy images to obtain residual image as
illustrated in Fig. 5. The residual image captures both
minor textures and noise. Feature vectors are extracted
from the residual images which are treated as
reference patches. To build edge patch based dictionary,
edge preserving filters are applied on high resolution
training images. The smoothed image is subsequently
subtracted from the original image to obtain an edge
image which captures the edges well. Feature vectors
are extracted from these edge images to build the edge
based global patch dictionary using the same process
discussed in Section II-D. Now for each reference
patch, similar patches are searched in the global edge
patch based dictionary to carry out NLM denoising.
Because of NLM, the noise is removed.

![Illustration of the process of edge patch based dictionary building.](image)

The step-wise denoising procedure for the edge
patch based dictionary is as follows.

a) Build the edge patch based dictionary: The
procedure for building the edge patch based dictionary is
same as that discussed in Section II-D.1 including the
various parameters such as feature vector, distance
matrics, threshold and branching factor. A complete
procedure for building an edge patch based dictionary is
shown in Fig. 6. However we treat dictionary building as
a preprocessing step i.e., we assume that before we start
the denoising process, the dictionary is available with us.

Average PSNR(dB) comparison for all test images
among the proposed method, the NLM method,
variants of the NLM method and the BM3D method
for different noise levels.
A. Results With Patch Based Dictionary

The comparative results for the test image when different numbers of patches from the dictionary have been selected. An improvement in the speed-up factor is observed as the number of patches selected from the dictionary is reduced, at the cost of less noise smoothing. It is possible to achieve a speed-up factor as high as 12.03 for the minimum number of patch selection but penalty is paid in terms of accuracy. We found that a choice of about 14 patches from the dictionary 180 patches would yield almost the same PSNR as the original NLM and yet offering a speed-up factor of 2.32. The effect of increasing the search window on NLM The proposed method is denoted as $NLM_{PD}$ and is independent of a search window as the patches are never searched in the window. From Table II we can clearly observe that, the advantage of the proposed method increases with increasing size of search window. When a full search space is used for NLM we have achieved a considerable improvement in terms of the speed. With the proposed $NLM_{PD}$ method speed-up factor as high as 1603 is achieved as compared to which is achieved with prefiltering based fast NLM methods. For the proposed $NLM_{PD}$ method, results are obtained with 100 patches.

Performance analysis using PSNR

The performance of our proposed method is compared in terms of PSNR with other denoising schemes, namely the original NLM method, the principal component analysis based NLM method (PCA-NLM), the patch regression based NLM method (NLM-Patch) and the BM3D method.

Table 4-1 and Table 4-2 show the comparative performance for Lena image and the average comparative performance for all test images at different noise levels, respectively. The bolded values represent the highest PSNR value among all of the algorithms for a given noise level. Figure 4-3 compares the average PSNR for the proposed method and all other denoising algorithms.

It has been found that, the proposed method performs better than all other methods except BM3D. In case of the BM3D method, the proposed method performs better than the BM3D method only when $\sigma < 50$. The BM3D method performs better at the higher noise levels.

PARAMETER ESTIMATION FOR DENOISING

Our proposed denoising framework, graphically outlined in Fig., requires us to infer various parameters from the observed noisy image. The procedure is algorithmically represented in Algorithm 1. We first identify geometrically similar patches within the noisy image. Once such patches are identified, we can use these patches to estimate the moments ($\mu$ and $C_{\mu}$) of the cluster, taking care to account for noise (steps 9 and 10 of Algorithm 1). Next, we identify the photometrically similar patches and calculate weights that control the amount of influence that any given patch exerts on denoising patches similar to it. These parameters are then used in to denoise each patch. Since we use overlapping patches, multiple estimates are obtained for pixels lying in the overlapping regions. These multiple estimates are then optimally aggregated to obtain the final denoised image.
Table 4-2: Average PSNR(dB) comparison for all test images among the proposed method, the NLM method, variants of the NLM method and the BM3D method for different noise levels.

<table>
<thead>
<tr>
<th>Noise Level</th>
<th>NLM</th>
<th>PCA-NLM</th>
<th>NLM-Patch</th>
<th>Proposed Method</th>
<th>BM3D</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>32.52</td>
<td>32.94</td>
<td>31.47</td>
<td>33.94</td>
<td>33.84</td>
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<tr>
<td>20</td>
<td>29.87</td>
<td>29.95</td>
<td>29.04</td>
<td>31.0</td>
<td>30.50</td>
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<td>28.26</td>
<td>27.45</td>
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<td>28.38</td>
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<td>40</td>
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<td>26.43</td>
<td>25.87</td>
<td>27.72</td>
<td>27.70</td>
</tr>
<tr>
<td>50</td>
<td>25.49</td>
<td>25.38</td>
<td>24.61</td>
<td>26.49</td>
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</tr>
<tr>
<td>60</td>
<td>23.85</td>
<td>23.87</td>
<td>22.75</td>
<td>24.30</td>
<td>25.94</td>
</tr>
</tbody>
</table>

Table 4-4: Average PSNR and average number of features comparison for patch size 5×5 for all test images between different threshold values for different noise levels.

<table>
<thead>
<tr>
<th>Noise Level</th>
<th>3</th>
<th>5</th>
<th>7</th>
<th>9</th>
<th>11</th>
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</thead>
<tbody>
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<td>10</td>
<td>PSNR 33.61 33.61 33.57 33.56 33.55</td>
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<td></td>
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<tr>
<td></td>
<td># of Features 24.17 23.5 23.17 22.83 22.17</td>
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</tr>
<tr>
<td>20</td>
<td>PSNR 30.38 30.37 30.36 30.33 30.31</td>
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<td></td>
<td></td>
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<tr>
<td></td>
<td># of Features 24.17 23.5 22.83 22.67 21.83</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>PSNR 28.65 28.64 28.61 28.60 28.59</td>
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<tr>
<td></td>
<td># of Features 23.83 23 22.67 22.5 21.83</td>
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</tr>
<tr>
<td>40</td>
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<td># of Features 23 22.67 21.83 21 20.83</td>
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Conclusion and future work:

Non-Local Means is a popular image denoising algorithm implemented in the spatial domain. In this thesis we have proposed a statistics based improvement for the Non-Local Means algorithm. The key of this improvement is to reduce the size of the feature space, which reduces the patch similarity measurement time and increases the overall denoising performance. We have utilized a statistical t-test to reduce the dimensionality of the feature space. This reduced feature space is used during denoising process. Our proposed scheme can be extended to video.

Our proposed scheme can be extended to video data. In that case, denoising a pixel will depend on the reference patch at time frame t and also on the same time frame t−1.

Color image denoising can also be considered as a future work. Instead of denoising the intensity value of the noisy pixel, luminance and chrominance information can be considered to denoise a color pixel. The proposed method can also be implemented in different applications.

REFERENCES