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AN EFFICIENT SCHEME FOR ROBUST IMAGE DENOISING USING PROBABLE NON LOCAL MEAN ALGORITHM

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Abstract— Here in this Paper a new algorithm probable nonlocal means (PNLM) method for image denoising. Our main contributions are Point out defects of the weight function used in the classic NLM methods, Successfully derive all theoretical statistics of patch-wise differences for Gaussian noise, Employ this prior information and formulate the probabilistic weights truly reflecting the similarity between two noisy patches. Our simulation results indicate the PNLM outperforms the classic NLM and many NLM recent variants in terms of the peak signal noise ratio (PSNR) and the structural similarity (SSIM) index. Encouraging improvements are also found when we replace the NLM weights with the PNLM weights in tested NLM variants.

Index Terms— denoising; local neighborhood; Non-local Means; PSNR; visual quality

INTRODUCTION

In the last few years, some very effective frameworks for image restoration have been proposed that exploit non-locality (long-distance correlations) in images, and use patches instead of pixels to robustly compare photometric similarities. The archetype algorithm in this regard is the Non-Local Means (NLM). The success of NLM triggered a huge amount of research, leading to state-of-the-art algorithms that exploit non-locality and the patch model in specialized ways. Non-Local Means (NLM) is a popular data-adaptive image denoising technique introduced by Buades. This technique is proven to be effective in many image denoising tasks and analyzes images on a patch-by-patch basis. Although the original NLM includes a weak Gaussian smoother, the weight is a simplified version with similar performance that is also widely accepted. Within the NLM framework, much progress has been made in recent years. Some authors have focused on fast NLM implementation, while others have explored NLM parameter optimization, or have adjusted the NLM framework to achieve better performance. The proposed algorithm is to shared interest of these three topics is the weight function of the NLM, which is the core of the NLM algorithm. Calculation of NLM weights is the most computationally expensive part of the algorithm and is related to many parameter optimization schemes. It has long been noticed that the NLM weight function is somewhat inadequate because it tends to give non-zero weights to dissimilar patches. However, the reason behind this inadequacy has not yet been fully explored. A study and analysis will be made in this research, how focus on the NLM weight function and propose a new probable solution.

PROBLEM STATEMENT

The aim of this research is to overcome the drawbacks of existing Non Local Mean algorithms, Here the research includes a new image denoising technique and how a simple extension and the improvement of de-noising performance of NLM, and even that of NLEM. A new algorithm named a "Probable Non Local Mean algorithm" is proposed for better performance.

OBJECTIVES

- To study and analyze the various image denoising algorithms includes Non Local Mean, Non Local Euclidean Median To find the efficient Image denoising method
- To improve the Performance analysis of image denoising algorithms i.e., considering the Peak Signal to Noise Ratio (PSNR) ,Structural Similarity Index (SSIM)
- We compare the PSNRs obtained using NLPR (p = 0:1) with that of NLM for some Standard natural images
- Note that, as expected, robust regression provides a much better restoration of the sharp Edges in the image than NLM

- The probably surprising is that the restoration is superior even in the textured regions. However, that NLM tends to perform better in the smooth regions

MOTIVATION

In the last few years, some very effective frameworks for image restoration have been proposed that exploit non-locality (long-distance correlations) in images, and/or use patches instead of pixels to robustly compare photometric similarities. The archetype algorithm in this regard is the Non-Local Means (NLM) [1]. The success of NLM triggered a huge amount of research, leading to state-of-the-art algorithms that exploit non-locality and/or the patch model in specialized ways; e.g., see [3], [4], [9], [5], [6], [7], [8], to name a few. We refer the interested reader to [2], [7] for detailed reviews. Of these, the best performing method till date is perhaps the hybrid BM3D algorithm [9], which effectively combines the NLM framework with other classical algorithms. To setup notations, we recall the working of NLM. Let u = (u_i) be some linear indexing of the input noisy image. The standard setting is that u is the corrupted version of some clean image f = (f_i),

$$u_i = f_i + \sigma z_i \quad (1)$$

Where (z_i) is iid $\mathcal{N}$(0, 1) The goal is to estimate (approximate) f from the noisy measurement u, possibly given a good estimate of the noise floor σ. In NLM, the restored image $\hat{u} = \hat{u}_i$ is computed using the simple formula

$$\hat{u}_i = \frac{\sum_{j \in S(i)} w_{ij} u_j}{\sum_{j \in S(i)} w_{ij}} \quad (2)$$

where w_{ij} is some weight (affinity) assigned to pixels i and j. Here $S(i)$ is the neighborhood of pixel i over which the averaging is performed. To exploit non-local correlations, $S(i)$ is ideally set to the whole image domain. In practice, however, one restricts $S(i)$ to a geometric neighborhood, e.g., to a sufficiently large window of size S x S around i [1]. The other idea in NLM is to set the weights using image patches centered on each pixel. In particular, for a given pixel i, let P_i denote the restriction of u to a square window around i. Letting k be the length of this window, this associates every pixel i with a point P_i in R^{k^2} (the patch space). The weights in standard NLM are set to be

$$w_{ij} = \exp\left(-\frac{1}{h^2}\left\|P_i - P_j\right\|^2\right) \quad (3)$$

Where $\left\|P_i - P_j\right\|$ is the Euclidean distance between P_i and P_j as points in R^{k^2} and h is a smoothing parameter. Along with non-locality, it is the use of patches that makes NLM more robust in comparison to pixel-based neighborhood filters [12], [11], [10].

Recently, it was demonstrated in [13] that the de-noising performance of NLM can be improved (often substantially for images with sharp edges) by replacing the ι^2 regression in NLM with the more robust ι^1 regression. More precisely, given weights w_{ij}, note that (2) is equivalent to performing the following regression (on the patch space):

$$\hat{P}_i = \arg min_P \sum_{j \in S(i)} w_{ij}\left\|P - P_j\right\|^2 \quad (4)$$

and the setting $\hat{u}_i$ to be the center pixel in $\hat{P}_i$. Indeed this reduces to (2) once we write the regression in terms of the center pixel $\hat{u}_i$. The idea in [13] was to use ι^1 regression instead, namely, to compute

$$\hat{P}_i = \arg min_P \sum_{j \in S(i)} w_{ij}\left\|P - P_j\right\| \quad (5)$$

and then set $\hat{u}_i$ to be the center pixel in $\hat{P}_i$, Note that (5) is a convex optimization, and the minimizer (the Euclidean median) is unique when k > 1 [14]. The resulting estimator was called the Non-Local Euclidean Medians (NLEM). A numerical scheme was proposed in [13] for computing the Euclidean median using a sequence of weighted least-squares. It was demonstrated that NLEM performed consistently better than NLM on a large class of synthetic and natural images, as soon as the noise was above a certain threshold. More specifically, it was shown that the bulk of the improvement in NLEM came from pixels situated close to edges. An inlier-outlier model of the patch space around an edge was proposed, and the improvement was attributed to the robustness of (5) in the presence of outliers.

SIGNIFICANCE

1. This research work will help us to find various image denoising algorithms.
2. Implementation of the algorithm and Mathematical analysis of the algorithm will be easy to find the appropriate result.
3. The amount of intelligence involved in the

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denoising will be highlighted

CONCLUSION

Image denoising and restoration of original image from the noise corrupted images will be a challenging task. Doing so there are so many algorithms have been proposed. This research aims in study and research of an efficient image denoising/restoration algorithms. After the study and analysis, if there are any drawbacks in the particular algorithm, suggestions will be given for improving the efficiency of denoising.

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