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REVIEW ARTICLE

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IMAGE PROCESSING USING SMOOTH ORDERING OF ITS PATCHES

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ABSTRACT

Now a days a number of image denoising techniques utilize patch information and interrelations between them to remove the noise. Although the ways of establishing the relations between patches may greatly differ depending upon the characteristics of noise and image. image processing scheme based on reordering of its patches. For a given corrupted image, we extract all patches with overlaps, refer to these as coordinates in high-dimensional space, and order them such that they are chained in the ”shortest possible path”, essentially solving the traveling salesman problem. The obtained ordering applied to the corrupted image, implies a permutation of the image pixels to what should be a regular signal. This enables us to obtain good recovery of the clean image by applying relatively simple one-dimensional (1D) smoothing operations (such as filtering or interpolation) to the reordered set of pixels. We explore the use of the proposed approach to image denoising and inpainting, and show promising results in both cases.

Keywords: Image Denoising, Patch Ordering, patch-based processing, inpainting, neural network.

1. INTRODUCTION

Recently, many image denoising techniques already presented works on the basis of the relations between neighborhood patches. Each one uses the different approach to estimate the relations between patches. Like weighted averaging of pixels, bunching the patches into disjoint sets and treating every set in a different ways etc. But the most popular one is creating a delegate dictionary for the patches and utilizing it form relations among the patches.

However every proposal uses the different ways of measuring relations between the patches the basic idea behind the all patch based technique remains the same. This idea states that each patch taken from the image might find comparative ones at somewhere

else in the image. In more general term we can say that, the image patches are expected to display an exceedingly organized geometrical frame in space framed by image.

This explanation describes why, non-local means can accomplish better results through joint treatment of comparative patches.

In this paper we set out an efficient approach to reduce the calculation time required for establishing relations between the patches, and on the other hand, we presented a weighted filter by utilizing the pdf of the image pixels.

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2. Literature Review

It has already been discussed in [4][5] that a number of the spatial domain denoising techniques are already presented in earlier work, like the bilateral filter [6], NLM (nonlocal means) [7], and optimal filtrations [8]. Broadly speaking, these denoising methods inherently share the same patch interrelations [9],differing mainly in the way the interrelation is calculated. Like in [1] [2] authors, use a wavelet domain to uncover complex relationship between patches of wavelet coefficients' from nearby spatial positions, at different orientations, and scales. On the other way, there are studies of image statistical properties which try to estimate an "optimal" set of linear vectors in the space defined by the image data. The patch searching methods have also been shown to have some modified versions. Such that presented in [17] for the nonlocal means(NLM) filter where an iterative version of NLM is motivated from considering an equivalent variational framework using gradient descent.

Adaptation of the NLM filter in a variational framework for image denoising and segmentation has also been done in [10] [11]. Learning a suitable basis function to describe image patches is another concept in same field. Use of such basis functions to describe geometric structure has been previously explored leading to the invention of curvelets[14], contourlets [15], bandelets [16], etc. All these tools allow learning of a suitable basis to describe the image, especially edge and texture regions .Many other linear and nonlinear methods have been also proposed to solve this problem. One of the earlier methods to achieve considerable success in this domain was the bilateral filter, proposed in [6]. While this method received broad attention in the image processing and computer vision communities, it fails to perform well in the presence of strong noise. A wavelet domain denoising technique based on scale mixture of Gaussians (GSM) proposed in [12] was considered to be better than all other techniques at the time of its introduction. In [7] proposed a simple patch-based technique which exploits the occurrence of repeating structures in a given image to perform a weighted averaging of pixels with similar structures to remove the noise. In [8], noticeably enhanced a localized version of this procedure using an iterative structure where the variance of the intensity estimation at each pixel location is used to compute the weights and the region of interest forth averaging process. A more recent technique named BM3D[13], works on the same concept of using similar patches throughout the image to perform denoising.

3. Problem Statement Image Denoising

Let Y be an image of size $N_1 \times N_2$where $N_1 N_2 = N$, andlet Z be its noisy version

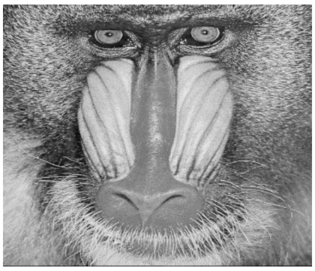
$Z = Y + V, \dots\dots\dots\dots\dots\dots\dots..(1)$

Vdenotes an additive white Gaussian noise independent of $Y$with zero mean and varianceσ^2. Also, let z and y be the column stacked representations of $Z$and Y, respectively. In order to reconstruct the original y from the noisy observation z we need a permutations matrix P_k of size $N \times N$ which arranges the elements of z in the order of their distances after that it is pass through an averaging filter H which produces the smoothed version ofz^s. Now the denoised y matrix is recovered by applying the inverse permutation $P_k^{-1}$to the result.

Image Inpainting

The problem of image inpainting consists of the recovery of missing pixels in the given image. Here we handle the case where there is no additive noise, therefore v = 0, and M is a diagonal matrix of size N ×N which contains ones and zeroes in its main diagonal corresponding to existing and missing pixels, correspondingly. Each patch may contain

Test images taken for the analysis (1) Hill



Test images taken for the analysis (2) Baboon,

Test images taken for the analysis (3) Lena

missing pixels, and we denote by Si the set of indices of non-missing pixels in the patch xi. We choose the distance measure between patches xi and xj to be the average of squared differences between existing pixels that share the same location in both patches.

Test images taken for the analysis (3) Boat

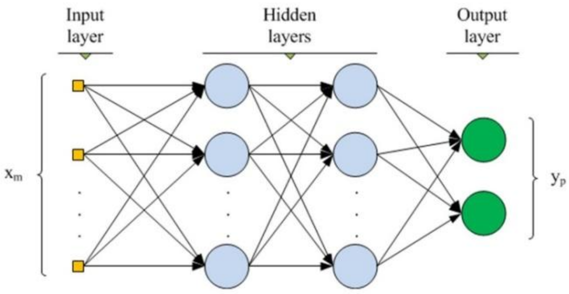
TABLE: Denoising results (PSNR in dB) of noisy versions of the images

Noise (σ^2)	10	20	50	80	100
Hill [19]	30.2015	28.1254	22.1182	13.2172	8.0287
Boat[19]	29.3210	27.1254	20.2434	12.765	7.9890
Lena [19]	35.9267	33.1167	25.4362	15.1058	8.2173
Baboon19]	35.6122	33.6148	25.3349	14.3724	8.5118

A curvelet based nonlocal means algorithm for image denoising is proposed in previous paper. The method determines the similarity of pixels in the noisy image based on the various levels of reconstructed images with complementary image features obtained by multi-scale curvelet transform or both these images and the noisy image according to the estimated noise stan-dard deviation in the noisy image. Extensive simulations have demonstrated that the proposed method outperform the state-of-art nonlocal means denoising methods in terms of noise removal and detail preservation because of its effectiveness in computing pixel.

CONCLUSION

This paper is over come denoising problem of images with the help of neural network.



Neural Network

Furthermore the ordering of patches requires the estimation noise-free value of patch which require heavy calculations. This paper presents an efficient approach to order the patch in a required sequence using the neural network. The neural network presents a coarse approximation of noise-free values of the patch. After that the weighted median filter is used to perform the smoothing operation which performs the final denoising. Finally the simulation of the proposed algorithm shows that the proposed scheme achieves much better results than many of state-of-the-art techniques.

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