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Nonlocal Means Based Image Filtering Using Similarity Validation

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Abstract:
Nonlocal means is one of the well-known and mostly used image denoising methods. The conventional nonlocal means approach uses weighted version of all patches in a search neighborhood to denoise the center patch. However, this search neighborhood can include some dissimilar patches. In this paper, we propose a pre-processing hard thresholding algorithm that eliminates those dissimilar patches. Consequently, the method improves the performance of nonlocal means. The threshold is calculated based on the distribution of distances of noisy similar patches. The method denoted by Similarity Validation Based Nonlocal Means (NLM-SVB) shows improvement in terms of PSNR and SSIM of the retrieved image in comparison with nonlocal means and some recent variations of nonlocal means.

INTRODUCTION

As digital imaging technologies become more advanced, the issue of image denoising still remains as a challenging stage. Removing additive noise is an essential pre-processing step in the majority of image processing techniques such as classification and object recognition, or it can be used for the purpose of improving image visual quality. Some of the earliest methods of denoising are simple averaging filters such as mean, median, Gaussian smoothing filters, and bilateral filters [1]. There are methods that transform data to other bases for the purpose of denoising such as wavelet or curvelet based methods [2]. The concentration of this paper is on nonlocal means methods (NLM) that are preferred when algorithm complexity is an issue. Most local methods only consider a local patch around the target pixel, assuming adjacent pixels tend to have similar patches. On the other hand, nonlocal means takes advantage of existence of a pattern or similar features in including the non-adjacent pixels [3]. NLM exploits self-similarities in the search neighborhood to estimate the true value of the noisy pixel. Since the introduction of NLM, many other variations have been proposed to further improve the method from various perspectives. For example, NLM with shape adaptive patches (NLM-SAP) is examined in [4]. The work in [5], improves NLM by a post processing denoising step based on method noise smoothing. Another recent improvement, probabilistic nonlocal means (PNLM) [6], implements a new weight function based on the distribution of the distances of similar patches. This weighting scheme outperforms the Gaussian kernel weights in traditional NLM. Regardless of the choice of the weights, many dissimilar patches in the search neighborhood are processed through NLM. Methods such as probabilistic early termination (NLM-PET) [7] attempt to reduce this number by a pre-processing hard-thresholding. However, the overall performance of this method is worse than that of the traditional NLM. A pre-filtering process is suggested in [8] to eliminate unnecessary patches by comparing gradient and average gray value of candidate similar patches. Motivated by the issue of unnecessary processing of dissimilar patches, we propose a new hard thresholding pre-processing algorithm to eliminate dissimilar patches before the weighting process. Our proposed method is faithful to the probabilistic distribution of the distance of similar patches. Our simulation results confirm superiority of this approach compared to the traditional NLM and the above variations of this method.

PROPOSED METHOD:

Our proposed method, denoted by similarity validation based nonlocal means (NLM-SVB), consists of three steps shown in Figure 1. In the following these three steps are explained in detail.

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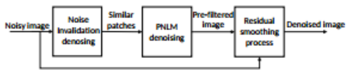

Fig. 1. Similarity validation based nonlocal means (NLM-SVB)

Step One:

Patch Similarity Validation Using fundamentals of NLM, for each reference patch the distance of that patch and the patches in searching area Si is first calculated. The goal is to keep similar patches in this area for further processing in next steps. Two patches are considered similar if their distance is only due to additive noise. Due to the nature of the distance, di , j in (3) this distance has a chi-squared distribution where the distribution for x is defined as:

$$y_i = x_i + n_i; \quad \forall i : n_i \sim \mathcal{N}(0, \sigma^2) \tag{1}$$

$$\hat{x}_i = \frac{\sum_{j \in S_i} w_{i,j} y_j}{\sum_{j \in S_i} w_{i,j}} \tag{2}$$

$$d_{i,j} = \|P_i - P_j\|_2^2; \quad w_{i,j} = e^{-d_{i,j}/h} \tag{3}$$

$$\chi_k^2(x) = \frac{x^{(k/2-1)} e^{-x/2}}{2^{(k/2)} \Gamma(k/2)} \tag{4}$$

where Γ denotes the Gamma function and k is the order of the distribution. Motivated by this definition of similarity in the first step, our goal is to hard threshold as many dissimilar patches as possible. The procedure is as follows: For any ith center patch, we first sort all the di,j s in its search neighborhood Si . In this case, similar patches with di,j s following Chi-squared distribution fall within a probabilistic boundaries that can be pre-calculated based on that Chi-squared distribution. Details of calculation of these boundaries are provided in Appendix 1. Using this probabilistic boundaries an example of the hard thresholding, that is also explained in Appendix 1, is as follows: Figure 2 shows the probabilistic bounds and sorted di,j s for three cases of a flat, an edge and a pattern search neighborhood respectively. Red squares show the reference patch Pi . Note that these boundaries are fixed for all three cases and only function of the σ and the size of Si . Consequently, the hard thresholding process considers any jth patch with its di,j out of this boundary as a dissimilar patch to the ith patch. For example, after sorting the patch distances, at index j = 1000 the probabilistic upper bound and lower bound with probability 99.8% (3σ probabilistic confidence) are 0.9114 and 0.6546. As the figure shows for the flat scenario, di,j at index j = 1000 is 0.8962, which falls within the boundaries. However, this value is 1.0116 and 1.1483 for edge and pattern scenarios respectively that are out of the boundaries. Therefore, 1000th sorted pixel is passed to step 2 for the first scenario, while being discarded (set to zero) for the second and third scenarios.

Step 2:

Weighting Process After elimination of dissimilar patches through the hard thresholding, the remaining patches are processed in the weighting stage. For this stage, our weights in (2) are consistent with the corresponding Chi-squared distribution in (4) [6]:

$$w_{i,j} = \chi^2_{\eta_{i,j}}(d^n_{i,j}/\gamma_{i,j}) \tag{5}$$

where:

$$\gamma_{i,j} = (2|P_i| + |O_{i,j}|)/2|P_i|; \qquad \eta_{i,j} = |P_i|/\gamma_{i,j} \tag{6}$$

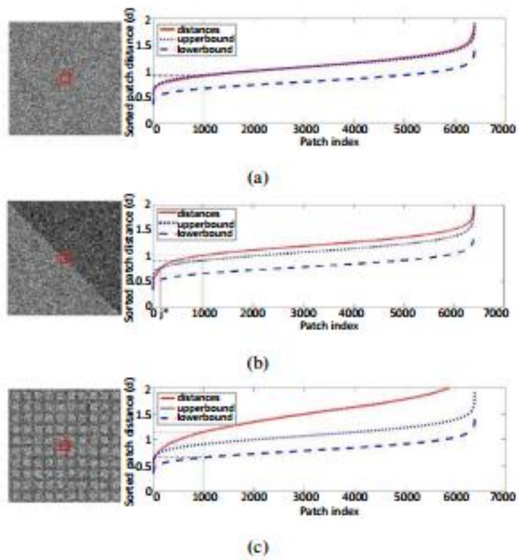

Fig. 2. Three scenarios of search neighbourhood Si: (a) flat, (b) edge, (c) pattern (σ=25). Little red square in the middle is Pi.

Right column: sorted distances of candidate patches, di,j s, and pre-calculated probabilistic boundaries in

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(16) and |Pi | is the number of pixels in Pi and |Oi,j | is the number of overlapping pixels between Pi and Pj . This step can be considered as a soft thresholding stage after a hard thresholding stage, both consistent and faithful to the exact distribution of di,j s for similar patches.

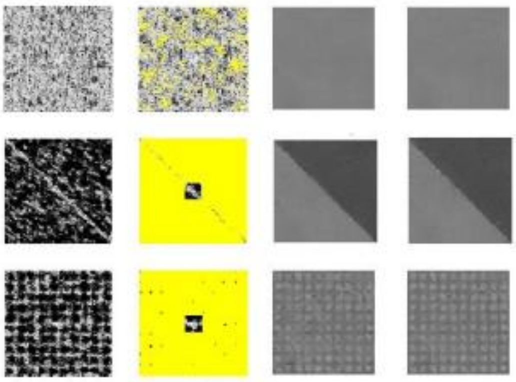

Fig. 3. For search neighbourhood Sis in Figure 2, First column: weights of PNLM,

Second column: weights of hard thresholding+PNLM, third and fourth columns: denoised versions of the images by PNLM and hard thresholding+PNLM respectively.

Advantages of pre-processing thresholding before weighting process: Figure 3 shows how our additional hard thresholding benefits the existing soft thresholding (PNLM) for the same scenarios as in Figure 2. The first column shows the associated weights of PNLM while the second column shows the weights for hard thresholding+PNLM. The additional zero weighted ones are shown in yellow in the second column. Comparing these two columns, the additional hard thresholding has zeroed the weights of many dissimilar patches (18% for flat case, 95% for edge case and 96% for pattern case). As the figures show, the remaining pixels are highly related (very similar) to the center pixel. The third and forth columns show the denoised results. As these two columns show elimination of the dissimilar patches resulted better denoised image, specially for the cases of edge and pattern structure, where with the additional hard thresholding fine details are well retrieved.

Step 3:

Smoothing Process This stage uses the conventional smoothing filter [9]:

$$\hat{x}_i^{new} = \hat{x}_i + \lambda D(y_i - \hat{x}_i) \qquad (7)$$

where D is the smoothing denoising function and λ is the added percentage of smoothed residuals. A mean filtering is applied over residuals, $y_i - \hat{x}_i$, [10]. For each pixel of the residual image, the mean value of pixels in a 3×3 neighbourhood is calculated to replace the center value and λ = 10% [5].

SIMULATION RESULTS:

Our test images are boat, man, cameraman, house, barbara and couple shown in Figure 4. The resulted percentage of patch elimination due to hard-thresholding for σ = 25 is provided in Table I. As the table shows, on average around 60% of patches are being discarded before the weighting process. Note that this percentage is higher in images with fine details such as man and barbara, while it is lower for images with less details such as house.

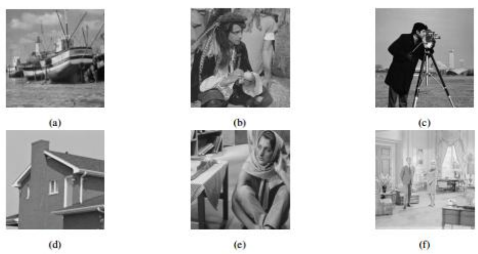

Fig. 4. (a) boat, (b) man, (c) cameraman, (d) house, (e) barbara, (f) couple

The quality measurement criteria used for the performance evaluation are PSNR [11] and SSIM [12]. The proposed method is compared to NLM and NLM-PET [7], NLM-SAP [4], Fast NLM [8] and PNLM [6] that are variations

CONCLUSION:

By adding an additional pre-processing stage in from of a hard thresholding, we have improved the performance of the traditional NLM. This pre-processing step attempts to eliminate dissimilar patches prior to the weighting process. As our simulation result shows this step can eliminate about 60% of the patches that are used in traditional NLM. As it was shown, this percentage is less for flat neighborhoods and more for neighborhoods with fine details. The proposed method (NLM-SVB) considers the exact distribution of similar patches distances in both the hard thresholding step and the weighting process. Our simulation results illustrate the advantages of the proposed method over the traditional NLM and some variations of NLM.

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