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Topics: Non-local means and Video denoising

Infrared image denoising by non-local means filtering

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Abstract

The recently introduced non-local means (NLM) image denoising technique broke the traditional paradigm according to which image pixels are processed by their surroundings. Non-local means technique was demonstrated to outperform state-of-the art denoising techniques when applied to images in the visible. This technique is even more powerful when applied to low contrast images, which makes it tractable for denoising infrared (IR) images. In this work we investigate the performance of NLM applied to infrared images. We also present a new technique designed to speed-up the NLM filtering process. The main drawback of the NLM is the large computational time required by the process of searching similar patches. Several techniques were developed during the last years to reduce the computational burden. Here we present a new techniques designed to reduce computational cost and sustain optimal filtering results of NLM technique. We show that the new technique, which we call Multi-Resolution Search NLM (MRS-NLM), reduces significantly the computational cost of the filtering process and we present a study of its performance on IR images.

Keywords: image denoising, non-local means, multi-resolution analysis

1. Introduction

Numerous IR imaging applications have been developed and deployed in fields that include the military, medicine and industry. However, relative low signal-to-noise ratio of IR imaging systems often limits the image quality and hinders their deployment. To enhance IR image quality, image denoising is often necessary.

Traditional paradigm image denoising is based on a local process involving the surrounding of the pixel to be denoised. In contrast, NLM denoising method[1] is based on the concept that any noisy pixel, located in the center of an image patch, may be denoised by building relevant statistics from patches with similar structure located anywhere in the image. It has been demonstrated[1] that the accuracy of this strategy is on the same level as state-of-the-art methods in general, and exceeds them in particular types of images, such as when applied to images having significant texture patterns.

There are many applications for NLM denoising technique. In Ref. 2 the authors were able to improve denoising significantly for ultrasound images using an NLM based technique. In Refs. 3, 4 the authors demonstrated better denoising results for computed tomography images, comparing to other known techniques. NLM was also used in Ref. 5, for denoising MRI images.

The main drawback of NLM is its relatively high computational cost. The image neighborhood feature vector is typically high-dimensional, e.g. it is 49 dimensional if 7X7 neighborhoods are used. In principle this vector is compared to all other vectors of similar size in the image. Hence, the computation of similarities between feature vectors incurs a large computational cost. Several techniques were developed to reduce this computational cost. For example, NLM with reduced similarity neighborhoods[1-3], preselecting similar patches based on first and second order statistics[6], NLM for textual pattern[7], and NLM with Probabilistic Early Termination[8] .Here we introduce a new efficient way to reduce the NLM processing time without reducing the searching area. The new technique is presented in Sec. 3.

The rest of the paper is organized as follows. In section 2, a brief review of NLM method is presented. In Section 3, we present the Multi Resolution Non Local Means (MRS- NLM) technique that we developed to reduce computational cost. In Section 4, NLM and MRS-NLM denoising results for IR images are presented. Finally, conclusions are in Section 5.

2. Image denoising with NLM filter

In this section we present briefly the NLM denoising technique, as first introduced by Buades[1]. Following Ref. 1 we represent the captured noisy image *y* as superposition of the denoised image obtained by applying the denoising operator D_h , and reminiscent noise term $\mathrm{n}(D_h y)$:

$$y = D_h\, y + \mathrm{n}\,(D_h y), \tag{1}$$

where h represents the filtering level. For a given image, *y*, the estimated value using NLM for pixel *i*, is calculated by using:

$$\mathrm{NLM[y](i)} = \sum_{\mathrm{j\epsilon I}} w(i,j) y(j), \tag{2}$$

where $w(i,j)$ is a weighting function, and $y(j)$ is the intensity of the pixel *j*. The weighting function, $0 \le w(i,j) \le 1$, compares the similarity between the patch surrounding the pixel *i* to be denoised to the patch surrounding an arbitrary pixel *j*. The weighting function is given by

$$w(i,j) = \frac{1}{Z(i)} e^{\frac{-\| \mathrm{y(Ni)} - \mathrm{y(Nj)} \|^2}{h^2}}, \tag{3}$$

where

$$Z(i) = \sum_j e^{\frac{-\| \mathrm{y(Ni)} - \mathrm{y(Nj)} \|^2}{h^2}}, \tag{4}$$

and $y(Ni)$ and $y(Nj)$ denote similarity windows or patches. The similarity between two pixels *i* and *j* depends on the similarity intensity grey level vectors, where $y(N_k)$ denotes a square neighborhood of fixed size and centered at a pixel *k* and is called the search area, *R*.

3. Multi Resolution Non Local Means

3.1 Multi resolution search process

The number of weighting functions calculated determines the NLM computational complexity. Calculation of $w(i,j)$ for n^2 pixels, leads to $n^2(n^2-1)$ Euclidian distance calculations. Under the assumption that each calculation takes $O(n^2)$ flops, the level of complexity, for example, for 512 pixels image, with R=21X21 search window and 7X7 similarity window, will be of $O(10^7 X n^2)$ flops. One of the popular ways to reduce the complexity is using a limited search area, R^1. Although limited search area is contrary to the basic concept of the NLM technique, there are several evidences that this can be useful and reduce the complexity by *R*.

To reduce the computational complexity of NLM while preserving the technique filtering result, we developed a new technique called Multi Resolution Search Non Local Means (MRS-NLM). The technique uses a multi resolution pyramid[10] as part of the pre-processing for NLM. Multi Resolution technique creates reduced-size images, using a convolution of Gaussian kernel. The ensemble of reduced images generates a Gaussian pyramid (Fig. 1). The pyramid levels, *l*, for the original image, y_0 with C_0, R_0 elements are calculated by:

$$y_l = reduce(y_{l-1}), \tag{5}$$

$$y_l(c,r) = \sum_{m=-2}^{2}\sum_{n=-2}^{2} t(m,n) y_{l-1}(2c+m, 2r+n) t(m,n), \tag{6}$$

where $t(m,n)$ is

$$t(m,n) = \hat{t}(m)\hat{t}(n), \tag{7}$$

$$\sum_{m=-2}^{2} \hat{t}(m) = 1 \quad 0<l<N,\ 0<c<C_0,\ 0<r<R_0 . \tag{8}$$

We use the multi resolution images to perform coarse pre-selection of similar patches, *S*. For each similarity patch, we find the compatible similarity window (patch) in the reduced image. As part of the pre processing step, we calculate the mean in the reduced image:

$$mean(y_l(c,r)) = \left(\frac{1}{S/2^{2-L}}\right)^2 \sum_{c=-s/2^{2-l}}^{s/2^{2-l}} \sum_{r=-s/2^{2-l}}^{s/2^{2-l}} y_l(c,r) \tag{9}$$

Similar patches to $y_N(d,t)$ in the highest pyramid level are defined as those having a patch mean not closer than a given threshold, d_N, to that of the reference patch:

$$Y'_N = \{mean(y_N(c,r)) | y_N(c,r), y_N(d,t) \in y_N\}$$

$$Y'_{N-1} = \{mean(y_{N-1}(c,r)) \pm d_{N-1} | y_N(c,r), y_N(d,t) \in y_N\}. \tag{10}$$

Patches passing this threshold are considered similar patches candidates in the next pyramid level, Y'_{N-1}.

The above described procedure is repeated until reaching level l=0 of the pyramid. Ultimately, NLM estimate (2) is calculated based on the patches that passed from y_1 to y_0 :

$$\mathrm{MR}S\_\mathrm{NLM}[y_0](\mathrm{i}) = \sum_{\mathrm{j}\in Y'_0} w(i,j)v(j).$$

The MRS-NLM operation is illustrated in Figure 1. To reduced NLM complexity, MRS- NLM is trying to find similar patches in the upper pyramid level, before calculating the weights, *Wi* according to (3).

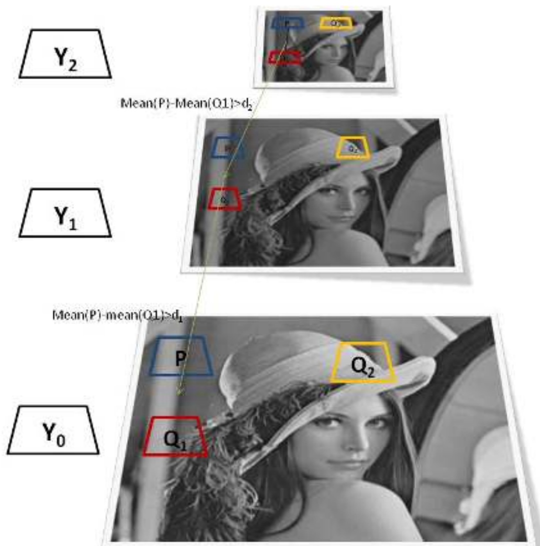


Figure 1: example of the MRS- principle. For each level in the pyramid, patches passing a certain threshold d_N, are transferred to the next level of the pyramid. For example, image patches P, Q1, moved to y_o after passing threshold d_2. These patches are ultimately used for the weighting function calculation in (3).

3.2 MRS- NLM results

MRS- NLM can be useful in those cases when NLM search area *R* should not be limited. In Ref. 1, Buades applied NLM with unlimited search area for handwrite image. In this case, using unlimited search becomes useful, since similar letters may appear anywhere in the image.

We compared NLM denoising techniques on a handwrite image, taken from Ref. 11, with different noise levels. To the original image we added white Gaussian noise with different levels, and compared the PSNR of the filter result to the original image. First, we used MRS- NLM with running parameters: patch size 7x7, d_1=7, d_2=50. Second, NLM with limited search area, based on the method described in Ref. 1 with parameters: patch size 7x7, search area *R* =70x70. Third, we applied NLM with the entire image as a searching are *R*, which we call full search NLM (FS-NLM). NLM denoising results where compared to those obtained with the Total Variation (TV) denoising technique, described in Ref. 11.

Comparative filtering results using various NLM denoising versions and TV filtering are shown in Figures 2 and 3Figure 2: Comparison of MRS-NLM technique to other denoising techniques. For noise level larger than 18 dB, the technique outperforms NLM with limited search area.. MRS- NLM used only 17% of the image patches, to compute *Wi*, which is approximately the same number of patches used with NLM with reduced search. It can be seen that for noise level larger than 18 dB, MRS-NLM technique outperforms NLM with limited search area. FS-NLM in these noise levels exhibit better denoising performance, but the complexity of the techniques rises by ~2X10[6].[9]

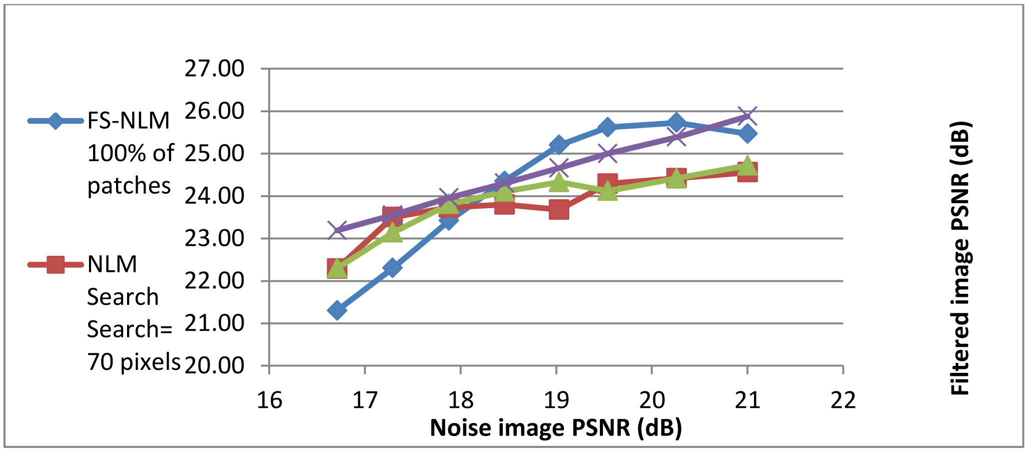
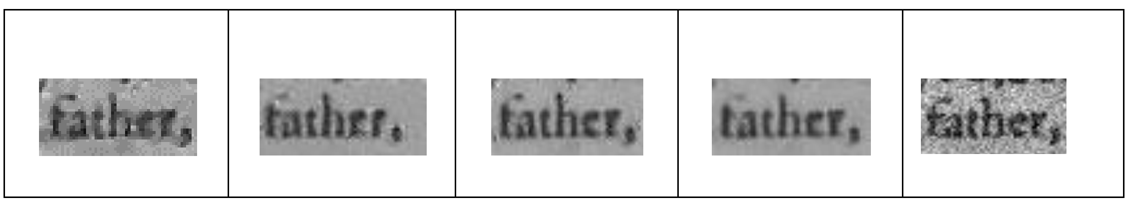


Figure 2: Comparison of MRS-NLM technique to other denoising techniques. For noise level larger than 18 dB, the technique outperforms NLM with limited search area.

Figure 3 shows a visual comparison between MRS-NLM, full search NLM (FS-NLM), restricted size NLM and TV denoising. It can be seen that MRS-NLM exhibits best visual results exile using computational effort as restricted NLM.



(a) (b) (c) (d) (e)

Fig. 3: Filt ults compariso ıdwrite image se level 19.03 to Right: (a) T ng result (PSNR=24.67 dB), (b) FS- NLM (PSNR=23.68 dB), (c) MRS-NLM (PSNR=24.33 dB), (d) FS-NLM (PSNR=25.02 dB), (e) original noised image (PSNR=19.03 dB).

4. The effectiveness of the NLM filter for IR image denoising

4. 1 Comparison of the NLM filter to common denoising filters

We compared NLM technique to common denoising techniques for images taken with IR images. NLM technique was compared to the following denoising techniques: Gaussian filter with kernel size of 3X3, and variance parameter 1, Bi-lateral filter taken from Ref. 12 with window size 5X5, σ_d=1, σ_r=50, wavelet filter, taken from Ref. 13 using hard thresholding and NLM filtering, taken from Ref.1, with patch size 11X11 and R=13X13. Representative results of digital filtering applied on images in the 8-14µm captured with Tadir thermal imaging system manufactured by ELOP Ltd. are shown in Figure 4. It can be seen that wavelet filtering and NLM preserved the image edges while filtering the noise. It can also be seen that the noise in the sky is filtered out while the edges at the top of the houses are preserved using NLM better than with wavelet filtering.

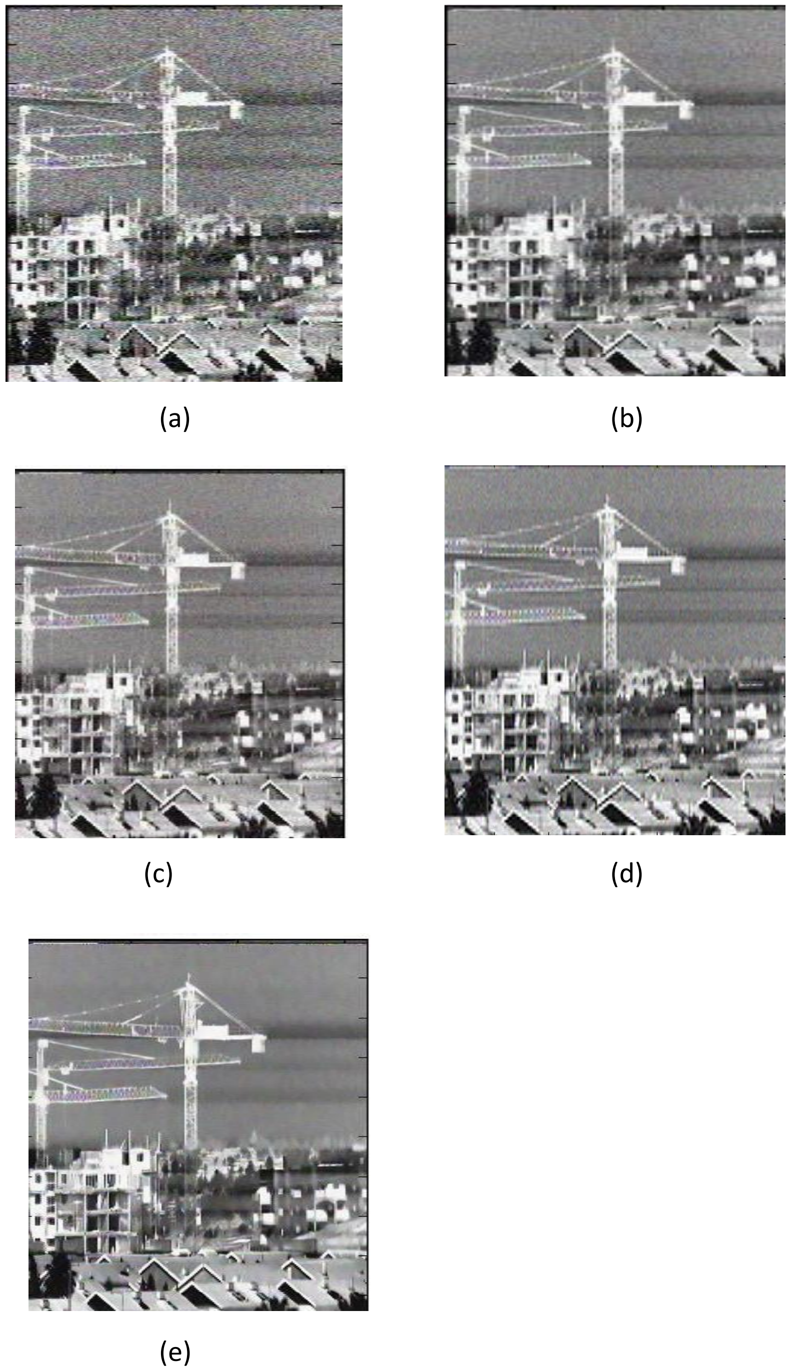


Figure 4: Comparison of various denoising techniques applied on an IR image. Left to right, Top to bottom: (a) Original IR image with Gaussian noise level=22. (b) Gaussian filter, PSNR=27.52 dB. (c) Bi literal filtering, PSNR=24.97 dB. (d) Wavelet filtering, PSNR=25.01 dB. (e) NLM filtering, PSNR=29.21 dB. Note that background noise and edge preserving is best using NLM.

4.2 Effectiveness of MRS-NLM for IR images

As explained in Sec. 2, MRS-NLM is particularly effective when a restricted area search yields sub-optimal performance and on the other hand full search is too computationally expensive. Therefore, we investigated the search window size required for representative IR images. Figure 5 shows representative results of the restoration PSNR versus the search window *R* size. It can be seen that increasing the search window above 100x100 does not provide additional image improvement. This result is not surprising; similar impact of the search area was found also in Ref. 14 for a large class of figures.

Figure 5 indicates that for typical IR image a full search is not necessary with NLM. Consequently, the MRS-NLM developed here has no particular advantage for the IR images examined; NLM with a limited search in a window up to 100x100 pixels is sufficient.

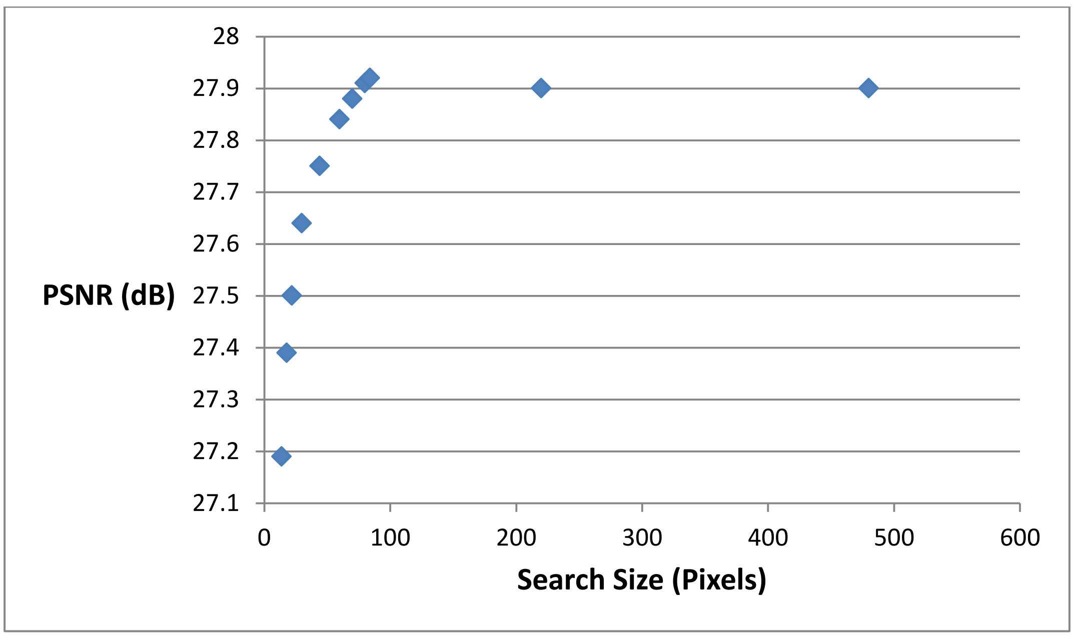


Figure 5: NLM Search range effect for IR images; restoration PSNR as a function of the search window size.

5. Conclusions

In this paper we investigated the application of NLM on IR images. We found that NLM gave best filtering results, in terms of PSNR, comparing to other techniques, such as Gaussian filter, bi lateral and wavelet transform. Visually, NLM filter preserved edges and filtered better background noise than the other techniques. We also presented an improved technique called MRS-NLM to reduce NLM computational complexity. MRS-NLM searches similarity patches in the entire image but with computational complexity much smaller than full-search NLM. However, since we found that for the examined IR images a full image search is not beneficial, MRS- NLM does not have particular advantage over common restricted search NLM when applied to IR images of the type we tested.

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