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Analysis of a Noisy Image by using External and Internal Correlations

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Abstract

In a single image denoising there is very limited data available for filtering it. In this paper, we propose novel image denoising scheme, which explores both external and internal correlation with the help of web images. In this paper we use two stage of filtering for removing the noise or for getting a noise free image. In the first stage we use graph cut based patch matching for improving patch matching accuracy in external denoising and use frequency truncation on internal cube in internal denoising. In the second stage of filtering process we use median filtering for both the external denoising and internal denoising for increasing the psnr value of an image as compared to previous model in which adaptive filtering is used in external denoising and wiener filtering is used in internal denoising.

Keywords: Image denoising, External filtering, Internal filtering, Datacubes, Linear method Nonlinear method.

INTRODUCTION:

Noise is considered as the data which have no clear output. Generally, it is sound, specially that one which is unpleasant or that causes disturbance. But in digital image processing, noise is something when more than half of the pixels of an image are replaced by random grey values ranging from white to black. Image denoising or image restoration or noise reduction are same kind of process in computer vision as well as digital image processing.For single instance, there are many methods which have been proposed to perform denoising, for the single image two important type of filtering is used.

a). Pixel level Filtering which comprises total variation regularization, bilateral filtering , Gaussian filtering etc.

b). Patch level filtering which comprises low rank regularization, non local means, block matching 3 D Flltering etc.

$$\textit{Denoising performance} \propto 1/(\textit{noise})$$

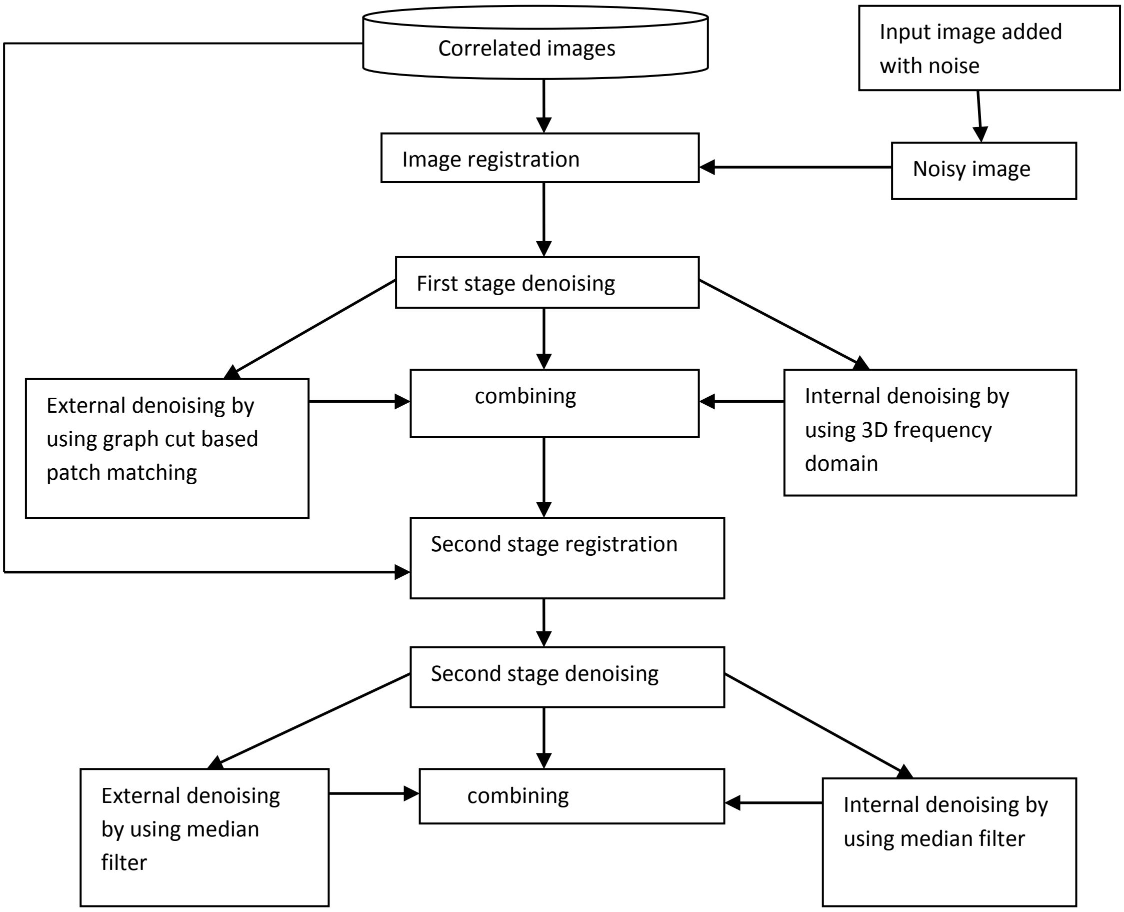
Image denoising is defined as the problem of recovering a natural image I from its noise-corrupted image IN. This problem has a rich history, with considerable progress made in recent years. In particular, the idea of using recurrence of small image patches within a natural image for denoising was first introduced in [1], and later extended by [2]). In these methods, each noisy image patch is denoised using other noisy patches within the noisy image. We refer to these as “Internal Denoising” methods. Other recent patch-based denoising methods employ external clean natural image patches (or a compact representation of them) to denoise each patch (e.g., [3]). We refer to these as “External Denoising” methods. Internal and External denoising were previously compared by [4] in the context of the ‘Non-Local Means’ (NLM) settings [1]. They found Internal NLM to be superior to External NLM. However, their comparison assumed that the same method (Internal or External) was applied to all image patches. Applying the same method to all image patches is typically true for most denoising methods. In this paper we show that some image patches inherently prefer Internal Denoising, whereas other patches inherently prefer External Denoising. Combining the best of both should thus lead to better results. We analyze and quantify the Internal vs. External preference of small noisy patches pn , and show that it is tightly related to the ‘Signal-to-Noise-Ratio’ within the patch, denoted by PatchSNR(pn). This is the ratio between the empirical variance of the original clean patch p, and the empirical variance of the noise within its noisy patch pn. We show that patches with low PatchSNR (e.g., in smooth image regions) tend to prefer Internal denoising, whereas patches with high PatchSNR (e.g., edges, texture) tend to prefer External denoising. The reason for this dichotomic behavior is the tradeoff between noise-fitting vs. signal-fitting. Patches with low PatchSNR are dominated by the noise. Unconstrained External search tends to overfit their noise (as opposed to constrained Internal denoising). On the other hand, patches with high PatchSNR (e.g., edges, texture) are dominated by the signal. They are less prone to overfitting the noise in an unconstrained External search, yet, they have much better signal-fit in the external clean database. These tradeoffs are analyzed and quantified. Finally, we exemplify the power of the PatchSNR, by combining pairs of different Internal/External denoising methods using a simple threshold on the patchSNR value (estimated per patch from the noisy image). Such a simple combination provides results better than the current state of- the-art methods.

There are three types of denoising methods –

- **Internal denoising or single image based denoising –**In the internal denoising method noisy pixel is filtered by using its neighboring pixels not by using its correlated images such Gaussian filtering.
- **External denoising or learning based denoising-**In the external denoising method each noisy pixel is filtered by using its correlated images not by using its neighboring pixels.
- **Internal and External Combined denoising-** The single image based (internal) and learning based (external) denoising methods have complementary strengths. Therefore, they can be combined to improve denoising performance. I. Mosseri et al. propose classifying the patches into internal and external denoising according to patch's signal-noise-ratio (SNR)[5]. Previous work[6] presents a simple and effective frequency domain fusion method to combine the advantages of internal and external denoising results and achieves the best denoising result compared with stand-alone methods.

PROPOSED SYSTEM:

In the proposed system or model we use two stage filtering for denoising the image because single image denoising suffers from limited data collection. In our proposed system we firstly take a noisy image and finding its correlated images from web and then done a registration for maintaining a correlation between noisy image and web image. After that two stage filtering is done in each stage two types of denoising is done internal denoising and external denoising. In the first stage graph cut based patch matching is used for external denoising and 3D frequency domain is used for internal denoising. In the second stage median filter is used in both the internal and external correlation for increasing the psnr value.



MODULES:

1. Correlated Image Retrieval
2. Correlated Image Registration
3. Combined Image Denoising:The First Stage
4. Combined Image Denoising: The Second Stage

1. Correlated Image Retrieval :

Learning based denoising methods ignore content priors in a noisy image, which limits improvement in denoising performance. Therefore, we adopt content-based image retrieval technology, specifically the scale invariant feature transform (SIFT) based method proposed , to retrieve correlated images from a large-scale database, as our external dataset. Since a large scale SIFT feature may cover multiple small scale SIFT features, propose bundling one large scale SIFT with many small scale SIFT features, namely using a visual group as one retrieval unit . The visual group is much more robust than the quantized single SIFT feature because the relative positions of SIFT features are considered in matching. After matching all the visual groups extracted from the noisy image with those extracted from candidate images, we obtain a set of correlated images.

Fig. 1 presents the top three retrieved images for three noisy inputs. The results demonstrate that the retrieval method does a good job of finding correlated images of the same scene with different imaging configurations for both architecture and natural images.

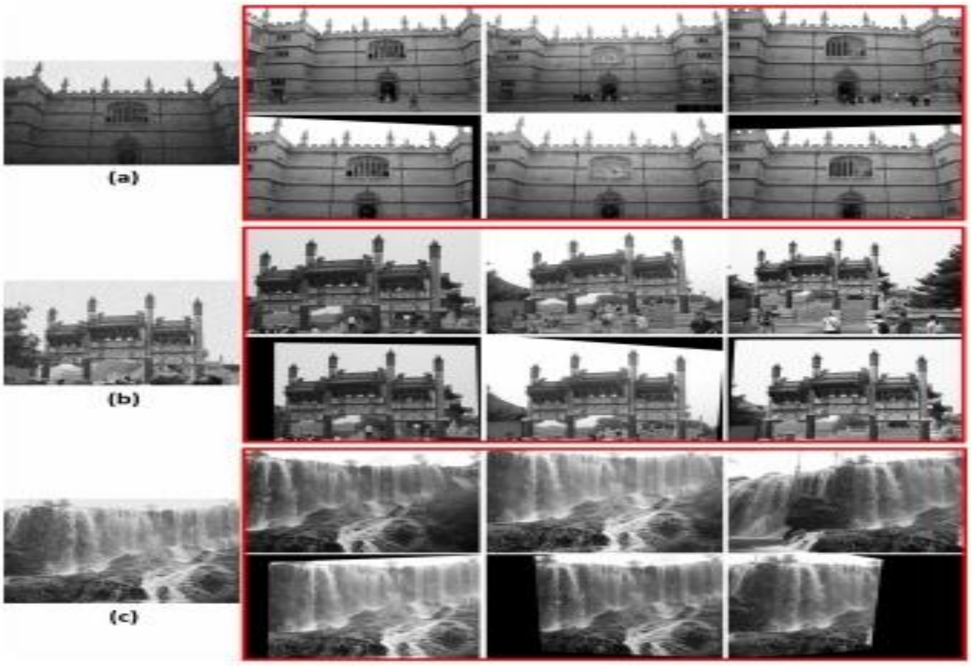


Fig.1. Retrieved Correlated Images

2. Correlated Image Registration:

Fig.1 presents the correlated images, though similar, are usually taken in different viewpoints, focal lengths and illuminations. Searching for matched patches from these images directly will not only impose considerable computational burdens, but also decrease the matching accuracy since the best matched patch may be at a different rotation and scale of the candidate patch. Although the patch matching algorithm proposed could search for patches across scales and rotations, it will result in an incorrect result because of the optimization process and the missing of true signal information with noisy query.

To solve this problem, we propose an approximate alignment through geometric registration to improve the correlation between the noisy query and retrieved images. First, we estimate the correspondences of feature points between the noisy image I and each of the correlated images. We adopt the matching criterion proposed and obtain a set of matching points, denoted as $X=\{x, x^r\}$, where x is the feature point in the noisy query, and x^r is its matched point in the retrieved image.

3. Combined Image Denoising: The First Stage

The noisy image I is split into overlapped patches {P} of size m×m at the step size of µ. For each noisy patch P, we aim to recover its details with the assistance of similar external and internal patches. Since P is heavily polluted by noise, searching for its similar patches in the external image set and the noisy image itself are both tough problems. Therefore, we propose a graph-cut based patch matching strategy to improve external patch matching accuracy, and using the first stage result to improve the internal patch matching in the second stage.

4. Combined Image Denoising: The Second Stage

The first stage denoising result $\tilde{I}^{1st}$ has greatly reduced the noise in I. Therefore it could help to improve the denoising performance in the second stage. A similar strategy is proposed in BM3D and have achieved significant gain compared with the first stage denoising result. In this section, we will first introduce median filtering in image denoising, and then apply it to our internal and external denoising scheme.

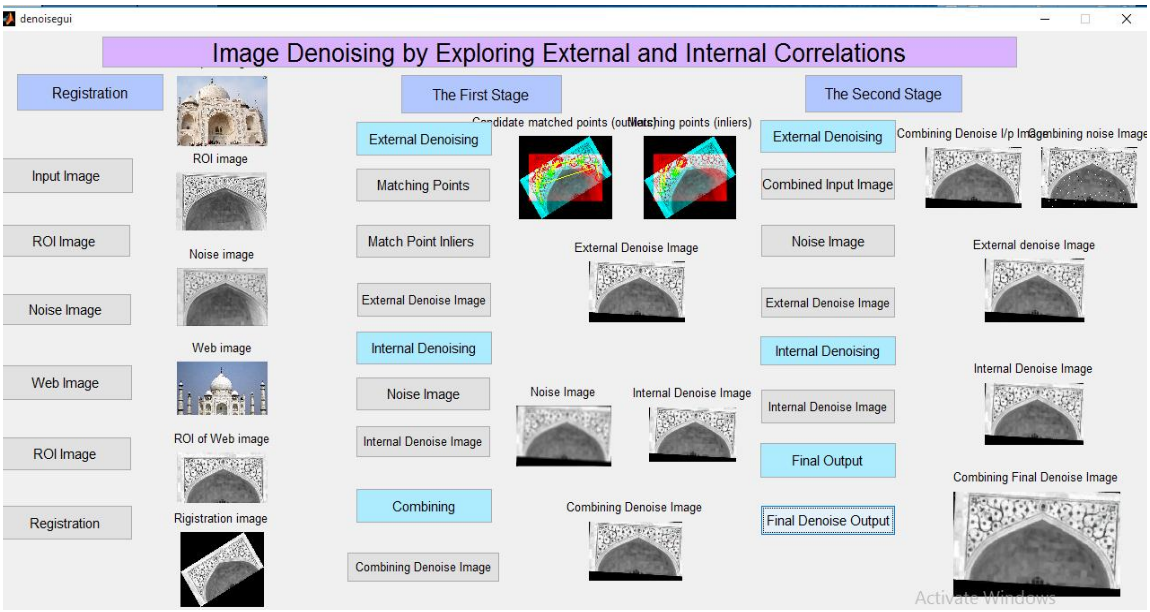
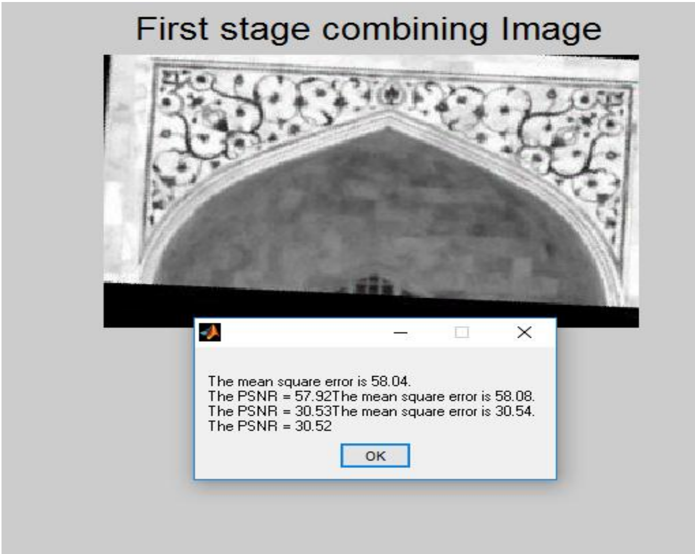


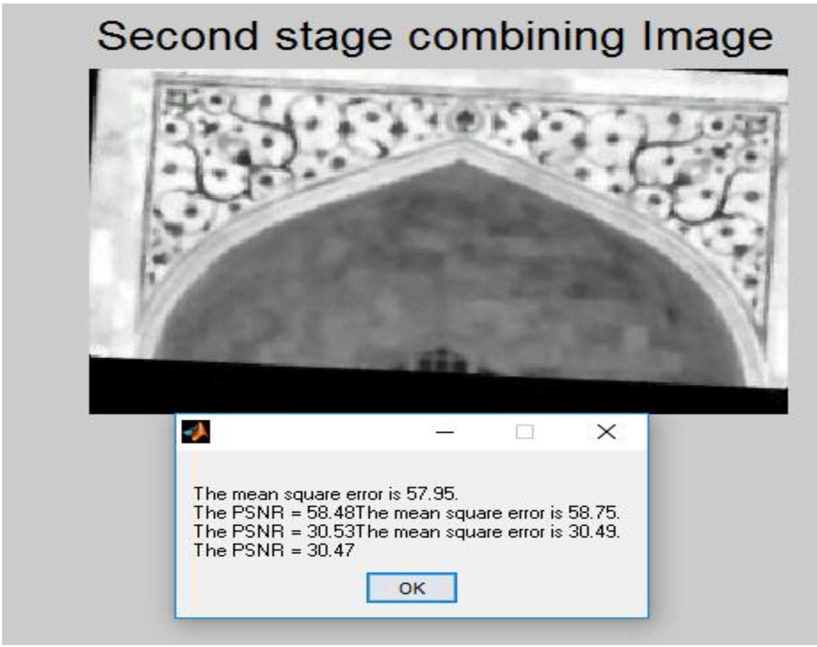
Fig. 2: Proposed system

In the previous model of this paper – In the second stage denoising there are two types of denoising is done internal denoising and external denoising. In the external denoising adaptive filter is used and in the internal denoising wiener filter is used. In our present approach we use median filter in both the internal and external denoising for calculating the image quality by their psnr value and mse value.

BEFORE ALTER IN THE PREVIOUS MODEL FIRST STAGE COMBINING IMAGE PSNR

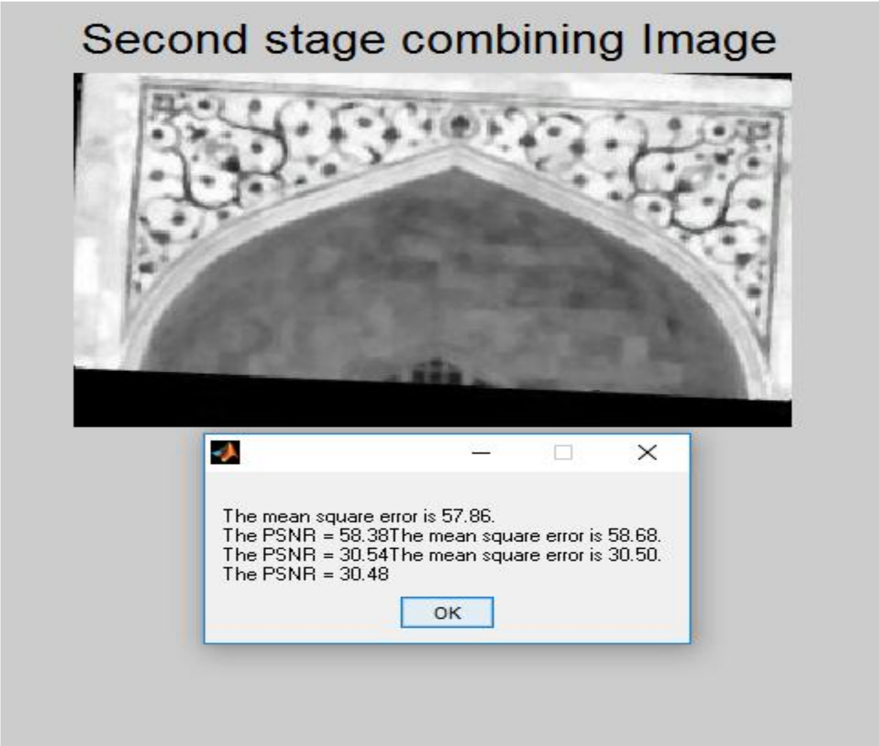


BEFORE ALTER IN THE PREVIOUS MODEL SECOND STAGE COMBINING IMAGE PSNR



AFTER ALTER IN THE PREVIOUS MODEL FIRST STAGE COMBINING IMAGE PSNR

AFTER ALTER IN THE PREVIOUS MODEL SECOND STAGE COMBINING IMAGE PSNR



CONCLUSION:

We have proposed a image denoising scheme by exploring internal and external correlations. Given one noisy image, we first retrieve its correlated images set from the web instead of using general image priors. Then in the first stage graph cut based patch matching is used as external denoising for improve patch matching accuracy. The internal denoising is performed within a noisy image there is no use of correlatd images and it done filtering in the transform domain. After combining the result of internal and external denoising in the transform domain we obtain a basic denoising result and the noise at the first stage is greatly reduced. Now in the second stage we use median filter for both the internal and external denoising for increasing the quality of an image that can be measure calculating the mse value and psnr value.

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