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Survey on Similarity Validation Based Image Denoising Methods

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Abstract- The need for efficient image restoration methods has grown with the massive production of digital images and movies of all kinds, often taken in poor conditions. No matter how good cameras are, an image improvement is always required. A digital image is generally encoded as a matrix of gray-level or color values. Image denoising is a main problem in image processing and is defined as a process aiming to recover an original clean image from its observed noisy version. Removing noise is an essential and the most fundamental pre-processing step in majority of image processing techniques such as medical and radar image analysis, image segmentation, visual tracking, classification and 3D object recognition, nonlocal means image denoising where obtaining a good estimate of the clean image is crucial for strong performance, or it can only be used for the purpose of improving images visual quality. This work briefs a survey on similarity validation based nonlocal means image denoising methods also review literature on nonlocal image denoising.

Keywords - Image Denoising, Image processing, Nonlocal Means Image Denoising, Similarity Validation, Adaptive filtering.

I. INTRODUCTION

During the past few decades, several denoising techniques have been proposed. One of the earliest examples is median filter, where the value of the corrupted pixel is been replaced by the median value in a window, in order to estimate the noiseless version of the target pixel. The other one is the linear mean filter implemented by a convolution mask which replaces each noisy pixel with the average of itself and pixels around it in a neighbourhood [4]. The goal in some of these methods is to find a scheme to do weighting average instead of calculating simple mathematical mean. Weights are based on similarity between pixels. In general case, the spatial distance (relative location of the pixels) and the photometric distance (the difference in intensity values of the pixels) both affect this similarity measure. How to take into account these two impacts introduces different denoising algorithms.

The classical one is Gaussian smoothing filter. They compute weights only by spatial Euclidean distance between pixels in form of a Gaussian kernel. Lack of considering the structural (photometric) similarity in the image is the major drawback of this method. Another method is known as bilateral filters [5]. Authors proposed to consider both kind of distances in a separable manner. Weights are multiplication of two Gaussian kernels with two adaptable decaying parameters, one for spatial distance and the other for photometric distance. This approach has advantages over the previous one, however it is been shown that this filter still does not have good performance in low signal to noise ratio cases [6]. Another group of image restoration methods are through Bayesian filters. The main idea is to find the true image given the prior information of the noise and the observed noisy image. The challenge in this method is to find an appropriate prior [6].

Some methods known as patch based methods attempt to find those weights as a function of similarity between pre-defined shape patches around the target pixel rather than pixel-wise calculations. There are two categories in those methods, local and non-local methods. Most local methods only consider a local patch around the target pixel, assuming adjacent pixels tend to have similar patches.

On the other hand, non local approaches take advantages of existence of a pattern or similar features in including the non-adjacent pixels in the denoising process [2]. Non-local means (NLM) originally introduced in 2005 by Budaes et al., exploits self-similarities in the search neighbourhood to estimate the true value of the noisy pixels. Due to its relative simplicity, NLM is the most well known and used spatial domain denoising methods, specifically when algorithm complexity is an issue [7]. This method is one of the concentrations of this work and will be introduced in the next chapter with more details.

II. NON-LOCAL MEANS ALGORITHM

Image denoising can be performed either in the frequency domain or in the spatial domain. In case of frequency domain, an image is transformed into the frequency domain, the denoising operations are performed there, and the resulting denoised images are transformed back into the spatial domain.

Perhaps the Block-Matching and 3D (BM3D) scheme is one of the most successful image denoisign algorithms that operates in the frequency domain. It relies on the assumption that an image has a locally sparse representation in its transform domain. It attempts to find similar blocks with respect to a reference patch and builds a 3D stack of these 2D blocks. Then it applies 3D transform on the 3D stack and performs denoising. It then applies inverse 3D transform and return 2D estimate of the original image. Finally, collaborative filtering process gives a 3D estimation of the jointly filtered 2D blocks.

Spatial domain denoising works directly on the image data. One of the most successful spatial domain denoising scheme is the Non-Local Means algorithm. In the Non-Local Means algorithm a center pixel inside the reference patch is denoised by calculating a weighted average, where patches similar to the reference patch contribute into this averaging process.

Non-local means relies on the fact that natural images contain repetitive patterns. The repetition of similar patches in images are used to estimate a noise-free image.

In the Non-Local Means algorithm a discrete noisy image v={ v(j)|j ϵ I }, where I is the input image, can be denoised by the estimated value NL[v](i) for a pixel i. It is computed as a weighted average for all of the pixels in the image,

$$NL[v] = \sum_{j \in I} w(i,j)v(j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.1)$$

where, the weight w(i, j) depends on the similarity between the pixel i and the pixel j of the intensity gray level vectors $v(Ni)$ and $v(Nj$). Here, Nk is the square patch around the center pixel k. The weight is then assigned to value v(j) to denoise pixel i. The summation of all weight is equal 1 and each weight value w(i ,j) has a range between [0, 1]. To measure similarity between patches, the Euclidean distance between patches is calculated.

$$w(i,j) = \frac{1}{Z(i)} e^{\frac{||v(N_i)-v(N_j)||_2^2}{h^2}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.2)$$

Here, h is a smoothing kernel width which controls decay of the exponential function and therefore controls the decay of the weights as a function of the Euclidean distances.

$$Z(i) = \sum je^{-\frac{||v(N_i)-v(N_j)||_2^2}{h^2}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2.3)$$

III. LITERATURE REVIEW

SR. NO.	TITLE	AUTHORS	YEAR	APPROACH
1	Similarity Validation Based Nonlocal Means Image Denoising,	M. Sharifymoghaddam, S. Beheshti, P. Elahi and M. Hashemi,	2016	Propose a pre-processing hard thresholding algorithm that eliminates those dissimilar patches.
2	Nonlocal means image denoising based on bidirectional principal component analysis,	H. H. Chen and J. J. Ding,	2015	unlike conventional principal component analysis (PCA) based methods, which stretch a 2D matrix into a 1D vector
3	Active matching for patch adaptivity in nonlocal means image denoising	S. Zhang, H. Jing and Y. Zhou,	2015	Presents a novel adaptive nonlocal means filtering scheme
4	Fast log-Gabor-based nonlocal means image denoising methods	S. Zhang and H. Jing,	2014	Explores the possibility of incorporating log-Gabor features into nonlocal means image denoising framework.
5	Denoising of 3D Magnetic Resonance Images Using Image Fusion	V. N. P. Raj and T. Venkateswarlu,	2014	An Image fusion based version of the Block wise Non-Local (NL-) means filter
6	Denoising of MR images using adaptive multiresolution subband mixing	V. N. P. Raj and T. Venkateswarlu,	2013	an algorithm based on Blockwise Non-Local (NL-) means filter and Dual Tree Comlex Wavelet Transform (DTCWT)

7	A novel improved median filter for salt-and-pepper noise from highly corrupted images	Changhong Wang, Taoyi Chen and Zhenshen Qu,	2010	a novel improved median filter algorithm for the images highly corrupted with salt-and-pepper noise

M. Sharifymoghaddam, S. Beheshti, P. Elahi and M. Hashemi,[1] 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 neighbourhood to denoise the center patch. However, this search neighbourhood can include some dissimilar patches. In this letter, 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.

H. H. Chen and J. J. Ding,[2] In this research, a very efficient image denoising scheme, which is called nonlocal means based on bidirectional principal component analysis, is proposed. Unlike conventional principal component analysis (PCA) based methods, which stretch a 2D matrix into a 1D vector and ignores the relations between different rows or columns, adopt the technique of bidirectional PCA (BDPCA), which preserves the spatial structure and extract features by reducing the dimensionality in both column and row directions. Moreover, also adopt the coarse-to-fine procedure without performing nonlocal means iteratively. Simulations demonstrated that, with the proposed scheme, the denoised image can well preserve the edges and texture of the original image and the peak signal-to-noise-ratio is higher than that of other methods in almost all the cases.

S. Zhang, H. Jing and Y. Zhou,[3] Baseline nonlocal means denoising scheme may be improved by incorporating more adaptivity, like locally varying filtering window, smoothing constants and patch size or shape. In this research, presents a novel adaptive nonlocal means filtering scheme, the key idea of which is that before computing the similarity between two pixels, active matching is performed to determine optimally matched patch shape and size. Systematic analysis and detailed simulation results show that the proposed algorithm achieves excellent trade-off between bias and variance, and obtains superior denoising performance compared with the state of the art.

S. Zhang and H. Jing,[4] This research explores the possibility of incorporating log-Gabor features into nonlocal means image denoising framework. It is found that log-Gabor features are better choice for this task than previously studied geometrical features. Moreover, combine log-Gabor features with original image patch information to arrive at mixed similarity measure, which leads to further denoising performance improvement. In addition, test a random projection-based approach to nonlocal means speed-up, guided by the well-known Johnson-Lindenstrauss lemma. Experimental results are quite encouraging.

V. N. P. Raj and T. Venkateswarlu,[5] In this research, an Image fusion based version of the Block wise Non-Local (NL-) means filter is proposed for 3D Magnetic Resonance (MR) image denoising. The filter is based on Dual Tree Complex Wavelet Transform (DTCWT)and sub band coefficient mixing. The image is filtered using block wise NL-means filter with two different sets of filtering parameters. The first set parameters were chosen to preserve the features in the image i.e. Less smoothing and feature oriented and the second set will do more smoothing i.e. noise oriented. Finally these two images are fused using DTCWT to remove the noise while preserving the sharp details in the image. The filter is designed for removing Gaussian and Rician noise from the image volume. Quantitative validation of the proposed method was carried out on Brain web datasets by using several quality metrics. The results show that the proposed filter performed well than the recently proposed filters based on 3D Discrete Wavelet Transform, Rician NL-means filters. The proposed filter removes noise effectively while preserving fine structures such as edges, lines etc. Even for very noisy cases.

V. N. P. Raj and T. Venkateswarlu,[6] In this research are proposing an algorithm based on Blockwise Non-Local (NL-) means filter and Dual Tree Comlex Wavelet Transform (DTCWT) for 3D Magnetic Resonance (MR) image denoising. The idea of the proposed filtering is adaptive subband coefficient mixing. The image is filtered using blockwise NL-means filter with two different sets of filtering parameters. The first set parameters were chosen to preserve the features in the image i.e less smoothing and feature oriented and the second set will do more smoothing i.e noise oriented. Finally these two images are fused using DTCWT and adaptive subband coefficient mixing to remove the noise while preserving the sharp details in the image. The filter is designed for removing Gaussian and Rician noise from the image volume. Quantitative validation of the proposed method was carried out on Brainweb datasets by using several quality metrics. The results show that the proposed filter performed well than the recently proposed filters based on 3D Discrete Wavelet Transform, Rician NL-means filters. The proposed filter removes noise effectively while preserving fine structures such as edges, lines etc. even for very noisy cases.

Changhong Wang, Taoyi Chen and Zhenshen Qu,[7] This research proposes a novel improved median filter algorithm for the images highly corrupted with salt-and-pepper noise. Firstly all the pixels are classified into signal pixels and noisy pixels by using the Max-Min noise detector. The noisy pixels are then separated into three classes, which are low-density, moderate-density, and high-density noises, based on the local statistic information. Finally the weighted 8-neighborhood similarity function filter, the 5×5 median filter and the 4-neighborhood mean filter are adopted to remove the noises for the low, moderate and high level cases, respectively. In experiment, the proposed algorithm is compared with three typical methods, named Standard Median filter, Extremum Median filter and Adaptive Median filter, respectively. The validation results show that the proposed algorithm has better performance for capabilities of noise removal, adaptivity, and detail preservation, especially effective for the cases when the images are extremely highly corrupted.

IV. PROBLEM STATEMENT

Non-Local Means is the most well-known image denoising method and has proved its ability to challenge other powerful methods such as wavelet based approaches or variational techniques. It is relatively simple to implement and efficient in practice. It is very similar to bilateral denoising method, considering both geometric and photometric distance of pixels. However it takes advantage of similarity between pixels far from the target pixel (non local) in addition to neighbourhood (local) pixels. It process the similarity measure over a square sub-image around two candidate pixels called patch. Similar to previous methods patches with higher similarity measures will have higher weight

Regardless of the choice of the weights, many dissimilar patches in the search neighbourhood are processed through NLM. Methods such as probabilistic early termination (NLM-PET) 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, propose a new hard thresholding pre-processing algorithm to eliminate dissimilar patches before the weighting process in [1]. 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 improves NLM by a post processing denoising step based on method noise smoothing.

V. CONCLUSION

In this research work, various well-known and used image denosing techniques has been studied the two most of them are: Nonlocal Means (NLM) and Block Matching 3D Transform Domain Collaborative Filtering (BM3D). It observed from survey that a nonlocal mean filter is quite good at image denoising since they take nonlocal information into account. An image is divided into overlapping patches and the algorithm identifies patches which are similar and use those in its attempt to denoise. The nonlocal mean filter can also be viewed in terms of diffusion maps and incorporated the idea of rotation-invariant distances in nonlocal mean filter to better identify patches which are closer. Adapt rotation-invariant distance not only to traditional nonlocal mean filter but also to the nonlocal median filter which is more robust to noise, and implement suggestions from current literature concerning diffusion maps along with rotation-invariant distance to see if can improve the idea of nonlocal mean filter further.

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