# An Extensive Survey on Image Denoising Method Based On PM Model with Transforming Edge Stopping Function

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***Abstract- over a last decade, the digital images have invaded our everyday life. Numerical cameras make it possible to directly acquire and handle images and film. Their quality is now equivalent to and often higher than for images obtained through photochemical processes. Digital images are much easier to transmit, improve on, and store on data- processing supports. There are two main limitations of digital image processing system is image accuracy are categorized as blur and noise. Blur is intrinsic property to image acquisition systems, as digital images have a finite number of samples and must satisfy the Shannon–Nyquist sampling conditions. The second main image perturbation is noise. This exploration presents image denoising method based on PM model with transforming edge stopping function.***

***Keywords- Nonlocal Means Filter, Similarity Validation, Image Denoising, Hard thresholding, Image Processing, Image Restoration PM Model, Edge Stopping Function.***

## I. INTRODUCTION

Image denoising is the problem of finding a clean image, given a noisy one. In most cases, it is assumed that the noisy image is the sum of an underlying clean image and a noise component, seeFigure 1.1. Hence image denoising is a decomposition problem: The task is to decompose a noisy image into a clean image and a noise component. Since an infinite number of such decompositions exist, one is interested in finding a plausible clean image, given a noisy one. The notion of plausibility is not clearly defined, but the idea is that the denoised image should look like an image, whereas the noise component should look noisy. The notion of plausibility therefore involves prior knowledge: One knows something about images and about the noise. Without prior knowledge, image denoising would be impossible.


Figure 1.1 A noisy image is assumed to be the sum of an underlying clean image and noise.

One can think of an image as a point lying in a high-dimensional space. Hence, image denoising involves moving from one point in a high-dimensional space (the noisy image), to a different point in the same space (the clean image) which is unknown a priori. Usually, it is impossible to find the clean image exactly. One is therefore interested in finding an image that is close to the clean image. In Figure 1.2, the denoising problem is illustrated using the A2-norm as a measure of closeness. In the figure, each point represents an image. All the images lying on the circle around the clean image have the same A2-distance to the clean image. However, some images on the circle are more desirable than others: The image lying on the straight line between thenoisy image and clean image is the most desirable because it contains no new artifacts (i.e. no artifacts that are not contained in the noisy image). This is due to the fact that the noise is assumed to be additive. All other points on the circle contain some new artifacts. Usually, it is impossible to find a point lying exactly on the line between the noisy image and clean image. Hence, denoised images almost invariably contain artifacts not contained in the noisy image. During denoising, one ideally seeks to introduce artifacts that are the least visually annoying. However, it is not clear how to define a measure or "visual annoyance",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. Each one of the pixel values Yi is the result of a light intensity measurement, usually made by a charge coupled device (CCD) matrix coupled with a light focusing system or a complementary metal oxide semiconductor (CMOS). Each captor of the sensor is roughly a chamber in which the number of incoming photons is being counted for a fixed period corresponding to the obturation time.

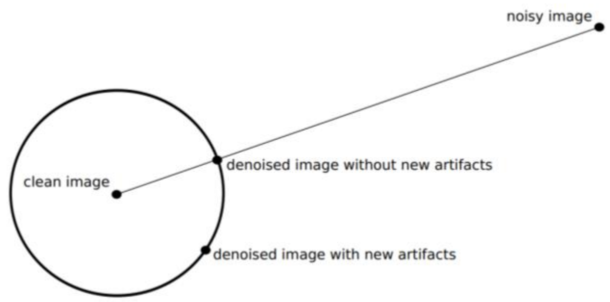


Figure 1.2 Illustration of Denoising Problem.

The two main limitations in image accuracy are categorized as blur and noise. Blur is intrinsic to image acquisition systems, as digital images have a finite number of samples and must satisfy the Shannon–Nyquist sampling conditions. Moreover, each pixel value is a result of photon count over the respective sensor chamber, which also depends on chamber's area.

The NLM search region is usually a rectangular neighborhood, centered at the pixel of interest (POI), which may include pixels whose original gray value do not match the value of the original central pixel. Consequently, their participation in the weighted averaging process degrades denoising performance, even though they are assigned relatively small weights. To eliminate their effect, researchers, e.g, suggest creating an adaptive search-region, which excludes those dissimilar pixels.

In this work, a novel model-based method has reviewed which defines a set of similar pixels to the POI from the initial search region, using the statistical distribution of the dissimilarity measure. Moreover, to enhance the denoising, the NLM based method also adaptively assigns one of two patch-kernel types to each pixel, based on its local features. This patch-kernel is used for weight computation. Also show that the suggested NLM modification improves the standard NLM performance both quantitatively and qualitatively. This approach is parameter free, since it is model-based, and that is its main uniqueness compared to other suggested methods for an adaptive search region.

## II. NONLOCAL MEAN FILTER

In the presence of noise, the original pixel value is lost. Neighborhood filters (a class of filters to which the Non-Local Means filter is a member of) reduce the noise by selecting for each pixel i a set of pixels Si characterized by both spatial proximity and similar gray level values. These filters proceed by replacing the gray level value of i by the average over the set $S_i$.

The local mean filter algorithm does exactly this. For the $(i, j)^{th}$pixel p, it sets up a neighborhood window of size r × r centered at p and computes the weighted mean of all pixels within this window. The mean is then assigned to be the denoised value pt at the $(i, j)^{th}$

location of the image. Mathematically, given U (i, j) = $I_{m\times n}(i, j)$ + N (i, j),

$$\widehat{U}_{i,j} = \frac{1}{|N|} \sum_{(l,k)\in M} U_{l,k} W_{l,k}, \dots\dots\dots\dots\dots\dots (1)$$

where N is the neighbourhood window, $Nij :=$ $\{U_{l,k} | i - r \le l \le i + r, j - r \le k \le j + r$

r, for some odd r ∈ N>0}, |N | is the cardinality of N , $W_{l,k}$ is the chosen weight.

*a. Non-Local Means Algorithm*

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,

$$NL = [v](i) = \sum_{j\in I} w(i,j) v(j) \dots\dots\dots\dots\dots\dots\dots\dots (2)$$

where, the weight w(i, j) depends on the similarity between the pixel i and the pixel j of the intensity gray level vectors $v(N_i)$ and $v(N_j$ ). 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.

$$||v(N_i - v(N_j)||_2^2 \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (3)$$

The weight w(i, j) is computed as,

$$w(i,j) = \frac{1}{z(i)} e^{\frac{||v(N_i - v(N_j)||_2^2}{h^2}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (4)$$

Here, Z(i) is a normalization constant such that,

$$Z(i) = \sum_j e^{-\frac{||v(N_i - v(N_j)||_{2\sigma}^2}{h^2}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

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.

*b. Applications of Non-Local Means*

The Non-Local Means algorithm has been used in many applications. It has been used in medical imaging such as on

- MR brain image.
- CT scan image.
- 3D ultrasound imaging.
- Diagnosis of heart echo images.
- Video denoising.
- SAR image denoising.
- Surface salinity detection.
- Metal artifact detection.

## III. RELATED WORK

| SR. NO. | TITLE | AUTHORS | YEAR | APPROACH |
|---|---|---|---|---|
| 1 | Image denoising method based on PM model with transforming edge stopping | J. Yu, R. Zhai and J. Yie | 2017 | Analyze the effects of different edge stopping functions with regard to edge protection. |
| 2 | Image Denoising Using Quadtree-Based Nonlocal Means With Locally Adaptive Principal Component Analysis, | C. Zuo et al., | 2016 | An efficient image denoising method combining quadtree-based nonlocal means (NLM) and locally adaptive principal component analysis. |
| 3 | Similarity Validation Based Nonlocal Means Image Denoising | M. Sharifymoghaddam, S. Beheshti, P. Elahi and M. Hashemi, | 2015 | Reported a pre-processing hard thresholding algorithm that eliminates those dissimilar patches |
| 4 | Nonlocal means image denoising based on bidirectional principal component analysis, | H. H. Chen and J. J. Ding, | 2015 | A very efficient image denoising scheme, which is called nonlocal means based on bidirectional principal component analysis, is reported |
| 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 is reported for 3D Magnetic Resonance (MR) image denoising |
| 6 | Fast denoising for fluorescence image sequences in a nonlocal means framework | H. Bhujle and A. Gupta, | 2014 | A fast non-local means technique to denoise 3D image sequences acquired via fluorescence microscopy. |
| 7 | A nonlocal means based adaptive denoising framework for mixed image noise removal, | Z. Lin | 2013 | An improved nonlocal means (NL-means) to simultaneously remove impulse noise and Gaussian noise |
| 8 | 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) for 3D Magnetic Resonance (MR) image denoising has reported. |

J. Yu, R. Zhai and J. Yie [1] Owing to the anisotropic Perona-Malik(PM) diffusion model is often used for image denoising and enhancement, and in this model the diffusion rate is controlled by the edge stopping function, the significant shortcoming of PM model is the failure in preservation of sharp edges and textures. In this paper, we mainly analyze the effects of different edge stopping functions with regard to edge protection. By selecting an appropriate edge stopping function, the drawback of the PM model mentioned above can be overcome. Therefore, in this paper, the characteristics of several different edge stopping functions are discussed, and finally some guidance suggestions are given for how to choice appropriate edge stopping function and the corresponding gradient threshold K.

C. Zuo et al.[2]In this letter, an efficient image denoising method combining quadtree-based nonlocal means (NLM) and locally adaptive principal component analysis has presented. It exploits nonlocal multiscale self-similarity better, by creating sub-patches of different sizes using quadtree decomposition on each patch. To achieve spatially uniform denoising, a local noise variance estimator combined with denoiser based on locally adaptive principal component analysis has reported. Experimental results demonstrate that reported method achieves very competitive denoising performance compared with state-of-the-art denoising methods, even obtaining better visual perception at high noise levels.

M. Sharifymoghaddam, S. Beheshti, P. Elahi and M. Hashemi,[3]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, a pre-processing hard thresholding algorithm that eliminates those dissimilar patches. Consequently, the method improves the performance of nonlocal means has reported. 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, [4]In this exploration, a very efficient image denoising scheme, which is called nonlocal means based on bidirectional principal component analysis, is reported. 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 presented 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.

V. N. P. Raj and T. Venkateswarlu,[5]In this investigation, an Image fusion based version of the Block wise Non-Local (NL-) means filter is reported 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 reported 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.

H. Bhujle and A. Gupta,[6] In fluorescence live-cell imaging there is always a trade-off between image quality and cell viability. While avoiding photo bleaching and photo toxicity, light exposure time must be limited which results in low signal-to-noise ratio. A fast non-local means technique to denoise 3D image sequences acquired via fluorescence microscopy has presented. The commonly used non-local means filter for image sequences is computationally inefficient. Reduce the computational cost by carrying out the denoising in the lower dimensional subspace determined by principal component analysis (PCA). Image neighbourhoods are projected onto the lower dimensional subspace determined by PCA. A shot boundary detection as a preprocessing step to identify and form different shots with content-wise similar frames has used. It shows that the reported method reduces the computations in addition to improving the accuracy. Our results are also compared with other fast NLM based techniques.

Z. Lin,[7]Most existing image denoising algorithms can only deal with a single type of noise; however, real world images are typically contaminated by more than one type of noise during image acquisition and transmission process. Recently, nonlocal approaches got great success in removing Gaussian noise; however, they cannot deal with impulse noise due to their nature. In this work, reported an improved nonlocal means (NL-means) to simultaneously remove impulse noise and Gaussian noise. An adaptive mixed noise removal framework based on the improved NL-means is also introduced. Comparing with existing NL-means based mixed noise removal frameworks which remove one type of noise at a time; the reported framework can remove mixed noise simultaneously in a single step. Experimental results show that the reported denoising framework has better denoising performance for mixed noise; meanwhile it is much more efficient which makes future parallel optimization such as GPU optimization possible.

V. N. P. Raj and T. Venkateswarlu,[8]In this exploration reporting 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 reported 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 reported filter removes noise effectively while preserving fine structures such as edges, lines etc. even for very noisy cases.

## IV. PROBLEM IDENTIFICATION

Image denoising is one of the most essential tasks in image processing for better analysis and vision. There are many types of noise which can decrease the quality of images. In the presence of noise, the original pixel value is lost. Neighborhood filters (a class of filters to which the Non-Local Means filter is a member of) reduce the noise by selecting for each pixel,a set of pixels characterized by both spatial proximity and similar gray level values. These filters proceed by replacing the gray level value by the average over the set.The NLM algorithm is inspired by the neighborhood filters. It takes advantage of the high degree of redundancy in any natural image by assuming that every small patch in a natural image has many similar patches in the same image

## V. CONCLUSION

In this work an extensive review of literature has presented. Many researchers, presented numerous denoising schemes such asWavelet based thresholding, Wiener filtering etc. The Curvelet transform is introduced as non-adaptive multi-scale transforms that is especially popular in the image processing field. The NLM estimate a POI by using a weighted average of pixels located in a search region associated with that POI. The weights are exponential terms that are inversely proportional to the dissimilarity between a small neighborhood of the POI and a corresponding small neighborhood of pixels within the search region. Apart from NM Perona-Malik(PM) diffusion model is often used for image denoising and enhancement reviewed in this work

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