International Research Journal in Global Engineering and Sciences. (IRJGES)
ISSN : 2456-172X | Vol. 3, No. 4, Dec. - Feb, 2019
Pages 69-74 | Cosmos Impact Factor (Germany): 5.195
Received: 16.02.2019 Published : 28.02.2019

PARAMETER ESTIMATION OF MODIFIED NON LOCAL MEANS IMAGE DENOISING USING GENETIC ALGORITHM

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Abstract
Image denoising is the most recent problem in the image processing community. Recently non-local means methods are widely used. The non-local means method is computed weighted average of pixels across the whole image. The pixel weight is mainly based on the similarity between the neighborhoods around them. The analysis of non-local means filter is done in this paper. In non-local means the parameters weight and variance are fixed. In this some problem occurs with the boundary pixels. Therefore the proposed method is the automatic method to set the value of the parameters. The performances are evaluated by using the MSE and SSIM value.
Keywords: Image denoising, image processing, MSE, SSIM

1. Introduction

Non-local means is an algorithm in image processing for image denoising. Unlike local smoothing filters, non-local means does not update a pixel's value with an average those of the pixels around it. Instead, it updates it using a weighted average of the pixels calculated to be most similar to it, calculated by its distance in the image. The weight of each pixel depends on the distance between its intensity grey level vector and that of the target pixel. If compared with other well-known denoising techniques, such as the Gaussian smoothing model, the anisotropic diffusion model, the total variation denoising, the neighborhood and an elegant variant, the Wiener local empirical filter, the translation invariant wavelet thresholding, the non-local means method gives better result. Under this model the observed image is X, the result of adding noise n to the original image i.e noiseless image Z. The relationship at pixel i becomes: Xi=Zi+Ni. The process of image denoising is to estimate z while preserving its features such as edges and texture. Usually it involves high frequencies. For this nonlinear methods are developed. Recently Non local means method is used. Several non-local means methos are introduced. The idea of this method is to estimate , Zi, using weighted average of all pixels in the image. The weight value can be given as Wij. It measures the similarity between the neighborhoods centered at i and j. The behavior of non-local means is analysed. The graph cut method is used to show the connection of these methods and denoising performance. First

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by using symmetric images the limitations of NLM is shown. Then the automatic estimation of the parameter in the modified non local means can be based on the noise variance value.The proposed work is to set the automatic estimation of the parameter values in terms of the MSE and SSIM. The same performance is achieved in modified NLM based on one parameter noise variance. The performance of both methods is compared by using the graph formulation of the MSE value. The approach of Non Local Means filtering is based on estimating each pixel intensity from the information provided from the entire image and hence it exploits the redundancy caused due to the presence of similar patterns and features in the image. In this method, the restored gray value of each pixel is obtained by the weighted average of the gray values of all pixels in the image. The weight assigned is proportional to the similarity between the local neighborhood of the pixel under consideration and the neighborhood corresponding to other pixels in the image. Due to the nature of the algorithm, the most favorable case for the NL-means is the textured or periodic case. In this situation, for every pixel i, we can find a large set of samples with a very similar configuration. Natural images also have enough redundancy to be restored by NL-means. Flat zones present a huge number of similar configurations lying inside the same object. Straight or curved edges have a complete line of pixels with similar configurations. In addition, natural images allow us to find many similar configurations in faraway pixels. NL-means algorithm chooses a weighting configuration adapted to the local and non-local geometry of the image. This experiment has been simulated by adding a Gaussian white noise of standard deviation σ to the true image. The objective is to compare the visual quality of the restored images, the non-presence of artifacts and the correct reconstruction of edges, texture and details. The filtering parameter h has been fixed, when a noise of standard deviation σ is added.

2. Non-local means denoising

The NLM algorithm estimates the denoised value at pixel i; X_i, using a weighted average of all pixels in the image:

$$X_i=\sum_j W_{ij}X_j \quad \text{---------- (1)}$$

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Figure 1. Non-local means filter weight similarity

The weights W_{ij} reflect the similarity between pixels i and j based on the distance between neighborhoods around them. Let Ni and Nj be the neighborhoods of size (2K + 1) × (2K + 1) centered at pixels i and j, respectively. The restriction of the image x to a neighborhood Ni will be denoted as X(Ni).

The weight value can be given as

W_{ij}=exponential of - $\| X(Ni)- X(N_j)\|_2^2/\sigma^2$

Normalized weight function can be given as

$W^*_{ij}= W_{ij}/\sum_j W_{ij}$

$\sum_j W^*_{ij}=1$ and $0\leq W^*_{ij}\leq 1$

It finds the similarity across the whole image in the non-local nature. But there are two disadvantages in this method. One is computational complexity of searching similar neighborhoods across the whole image. Second is taking the weighted average across the whole image does not achieve good MSE value. This is critical along edges since pixels along them have less corresponding neighborhoods in the image.
Better solution may be obtained via averaging only pixels within the same neighborhood class. Therefore, the denoising performance depends in a good neighborhood classification. It is applied that NLM together with a restriction on the distance of neighborhoods being averaged for denoising. That is, for each pixel to be denoised it is considered that only pixels with neighborhood similarities greater than the threshold value, that is exponential of - $\| X(Ni)- X(N_j)\|_2^2/\sigma^2$. Second, we show that the best value of weight is the one that allows identifying the neighborhoods classes.
The error decreases with the increasing of the weight value. After it is concluded that the error in the boundary pixel is higher than the error in the non-boundary pixels. The best denoising performance is achieved when we correctly calculate the neighborhood pixels. So instead of changing the value of threshold weight value, the variance σ is changed. The improved NLM is achieved.

3. Modified Non-local means denoising

The automatic estimation of parameters σ and the weight value is addressed. The parameters are estimated as follows. The σ value is based on the noise variance.
For Gaussian noise the variance of this estimation is $\sigma=h\sigma_n$. h looking at the expected distances for neighborhoods inside the same class. The expected squared distance for two identical neighborhoods corrupted by Gaussian noise with zero mean and variance σ_n.

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The distance value can be obtained as
$d=2(2K+1)^2 \sigma_n^2$

The standard deviation of the square difference for these neighborhoods is $\sigma_d=(2K+1)^2 \sqrt{8}\sigma n2$. The σ should be proportional to $(2K+1)^2$ and σ_n^2.
The h value is set in order to obtain weights greater than the threshold weight value γ for similar neighborhoods. In this way the value of h is defined as the one that satisfies the following equation:

$\exp(-d^2/h^2 \sigma_n^2)$

then $h=\sqrt{(2(2K+1)^2/lod(1/\gamma))}$

Finally the new weight value is obtained as

$\exp(-d^2+ \sigma_d^2/2 /h^2 \sigma_n^2)= \gamma$

Thus the new value γ is introduced. The parameter does not depend on the input image but the variance σ. The neighborhood values obtained in the same classes.

2. Genetic algorithm

A genetic algorithm (or GA) is a search technique used in computing to find true or approximate solutions to optimization and search problems. Genetic algorithms are categorized as global search heuristics. Genetic algorithms are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (also called recombination). Genetic algorithms are implemented as a computer simulation in which a population of abstract representations (called chromosomes or the genotype or the genome) of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are selected from the current population (based on their fitness), and modified (recombined and possibly mutated) to form a new population.

3. Graph formulation of NLM

The graph is formulated between the value of weight value and the error value. So that the performance of the NLM and modified NLM can be evaluated.

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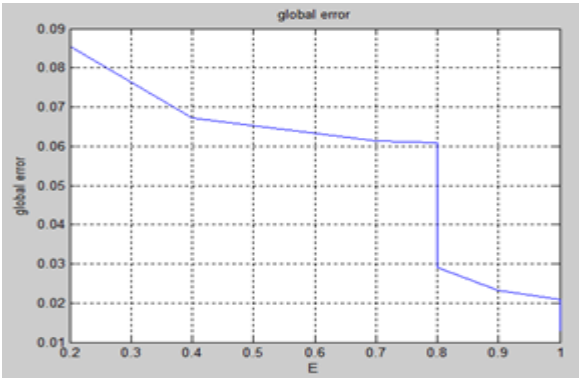

Figure2. Graph between the global error and the weight value

Figure 3. Original image, NLM image, MNLM image

IMAG	NLM (MSE)	MNLM (MSE	NLM (SSIM)	MNLM (SSIM
Lena	9.85189 e+01	9.634 e+01	9.31821 e-01	9.8284 e-01

Table1. MSE and SSIM value

4. Conclusion and future work

The performance of NLM and modified NLM is evaluated by using the variance and the weight values. It is concluded that the optimal result is obtained with the specific value of h. Both produce similar result in terms of SSIM and MSE. In the future work the optimal value of h is to be applied for the real images and various distance calculation methods can also be used for the calculation of the similarity neighborhood pixels.

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