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APPLICATION OF THE ALGORITHM OF PARAMETRIC AND NON-PARAMETRIC CONFIDENCE INTERVALS IN PRE-PROCESSING IMAGE DATA

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Abstract

Digital image processing and enhancement is one of the most important and frequently used issues in many fields of image processing. When handling images or sending them over a particular channel, they are subject to certain noise and require filtering methods. In this paper, the parametric confidence interval algorithm was compared to the nonparametric confidence interval algorithm for processing the noisy images. The results showed that a nonparametric confidence interval algorithm is better at defining the external parameters of an image in terms of noise elimination and enhancement landmarks.

Keywords: Image processing, image pre-processing, Image, Noise, parametric confidence interval, nonparametric confidence interval

I. Introduction

Statistical methods are a primary way to solve many problems that require estimating lost or uncertain information. One of the most important estimating methods is interval estimation, which is defined as the determination of an interval containing a set of values based on sample data and defined by two terms, minimum and maximum. Confidence limits are the frequency of sample size to reach the best estimates for the community parameter, as the larger the sample size, the closer it will be to the confidence limits; Because it reduces the standard deviation, we get an efficient rating. The Boundary of Confidence (Boundary of Confidence) and the Boundary of Infidelity (Boundary of Infidelity) are generally defined as estimating the community parameter from sample data by specifying a period containing a set of points. The Boundary of Infidelity (Boundary of Confidence) is more difficult because the Boundary of Infidelity is biased, so there will be a problem in measuring the Boundary of Estimation directly [II]. In this research, confidence limits were applied to an initial image processing process, also called filtration and resolution enhancement. An initial image processing function is to improve image quality without altering image parameters or increasing the information to be extracted from the image because it reduces noise and improves image quality before processing in any image processing process. Debriefing to be studied. Noise Gaussian is a natural noise from the Image Acquisition system in which the continuous electrical signal is digitized to the calculator and Speckle noise, a pocket-pattern amplification characteristic of ultrasound and SAR [VII]. After the image is initially processed using the parametric and non-parametric confidence intervals algorithm, the initially processed image is optimized and the two images are compared to see which image is better quality. A contrast enhancement is defined as how much difference is between different brightness of the image elements [X]. Illuminance sensitivity depends on the spatial distribution of the luminous and opaque areas of the image, and the brightness or brightness available when taking an image that expresses the amount of light reflected from or transmitted by the camera. The most important thing that affects image quality [VIII], is if the user has no experience in dealing with light and if the photographer pays attention to an image that is either dim or luminous resulting from a poor distribution of the images' colors due to lack of luminance in the vicinity of the photo when it is taken.

This research aims to employ the technique of cognitive and statistical non-parametric confidence limits in the image processing process initially, comparing the two methods using statistical measurements, improving image contrast on the images produced by the two methods, and finding out which of these methods were able to eliminate noise, as well as their ability to exhibit hidden features. As of 2018, Buenestado and Acho [1] developed a new method for dividing images based on a statistical trust boundary tool along with the well-known Otsu algorithm. In 2021, Jaber, Eesa, Aseel, and Bushra [4] split the image using the threshold in two stages where they treated the image with the parameter confidence boundary method initial treatment and then cut the image with the Bernsen's Thresholding technique.

The research has been structured as the same: the second section includes the parametric confidence interval algorithm. The third part includes the limits of cognitive trust. The fourth part contains the practical aspect of the research; the last part contains the conclusions that have been reached.

II. Image Pre-processing Based on Statistical Confidence Interval Algorithm

The method of the parametric confidence interval is one of the methods of estimating community parameters, where the estimated parameter is between the upper and lower limits of any determinant between a set of values between which the value of the parameter and the probability of having the value of the estimated parameter in this period is the degree of confidence $1-\propto$. When employing confidence limits in the initial processing of the image, the confidence interval of the arithmetic mean of the image data is estimated and found as follows:

$$p\left(-Z_{\frac{1-\alpha}{2}} < \frac{\bar{a}(i,j)-\mu_k(i,j)}{\frac{\sigma}{\sqrt{i_a j_a}}} < +Z_{\frac{1-\alpha}{2}}\right) = 1-\alpha \quad (1)$$

Simplifying the probability period we get:

$$p\left(\bar{a}(i,j) - Z_{\frac{1-\alpha}{2}} * \frac{\sigma}{\sqrt{i_a j_a}} < \mu_k(i,j) < \bar{a}(i,j) + Z_{\frac{1-\alpha}{2}} * \frac{\sigma}{\sqrt{i_a j_a}}\right) = 1-\alpha \quad (2)$$

Where:

$\mu_k(i,j)$: Is the arithmetic mean parameter of the population?

$\bar{a}(i,j)$: Estimated by the estimated mean parameter estimated by the confidence limit method.

The method can be represented by the following algorithm:

1. In the beginning, the images are inserted and the arithmetic mean m and standard deviation s are extracted from the image.
2. Split the original image into n_p of sub-images.
3. Through the Cartesian coordinate $\mu_k(i,j), k=1,\ldots,n_p$ which represents the average parameter of the density of the gray-frequency image unit for each given sub-image, the arithmetic mean is estimated $\bar{a}(i,j)$.
4. For each sub-image $\mu_k(i,j), k=1,\ldots,n_p$ the confidence limits are calculated according to the formula

The following:

$$p\left(\bar{a}(i,j) - Z_{\frac{1-\alpha}{2}} * \frac{s}{\sqrt{i_a j_a}} < \mu_k(i,j) < \bar{a}(i,j) + Z_{\frac{1-\alpha}{2}} * \frac{s}{\sqrt{i_a j_a}}\right) = 1-\alpha \quad (3)$$

III. Image Pre-processing Based on nonparametric Statistical Confidence Interval Approach

In this paragraph, the nonparametric confidence intervals are employed for initial image processing by estimating the parameter density function from the image data. The process of estimating the nonparametric confidence interval [3,2] is more difficult because the nonparametric is biased. There are several methods of estimating the nonparametric confidence intervals [XII]: Plug-in Approach, Bootstrap Approach, and Bootstrap and Plug-in Approach.

In this paper, the Plug-in Approach method will be dealt with, which is one of the simplest methods, where $\hat{f}_n(x)$ is replaced in the corresponding variance instead of $f(x)$ at a confidence score of $1-\propto$.

The confidence limits for x are mathematically the following:

$$p(f(x) \in C_{1-\propto}(x)) = 1 - \alpha \quad (4)$$

Where $C_{1-\propto}(x)$ the confidence region of the density functions, which are random intervals $C_{1-\propto}(x)$ are obtained from the sample data. We discussed the pulp estimator:

$$\hat{f}_n(x) = \frac{1}{nh_n} \sum_{i=1}^{n} K\left(\frac{x-x_i}{h_n}\right) \quad (5)$$

Whereas,

$\hat{f}_n(x)$: The estimated probability density function [11] is a continuous definite identifiable real function whose integral is equal to one, i.e. $\int K(u)\,du = 1$,
h: represents the bandwidth parameter. The optimal package width is chosen by relying on the Mean Integrated Square Error (MISE) [6]

$$\text{MISE}[\hat{f}(x,h)] = E\int[\hat{f}(x,h) - f(x)]^2\,dx \ \text{MISE}[\hat{f}(x,h)] = var\left(\hat{f}(x,h)\right) + \quad (6)$$

$$baise^2\left(\hat{f}(x,h)\right) \quad (7)$$

We take the state for one univariate and after the derivative of the variance and bias of the core function, then:

$$\text{MISE}[\hat{f}(x,h)] = n^{-1}h^{-1}R(K) + \frac{1}{4}h^4\mu_2(K)^2R((f)^2) \quad (8)$$

Where:

$$R(K) = \int (K(u))^2 du$$

$$\mu_2(K)^2 = \int u^2 K(u) du$$

$$R((f)^2) = \int [f''(u)]^2 du$$

Squared $\text{MISE}[\hat{f}(x,h)]$, and the derivative of h is given:

$$\hat{\text{h}}_{\text{MISE}} = \left[\frac{R(K)}{\mu_2(K)^2R((f)^2)}\right]^{1/5} \quad (9)$$

The final equation is the estimation of the bandwidth parameter of a single variable, and in the case of a multivariable the boot parameter is written as:

$$\hat{\text{h}}_{\text{MISE}} = \left[\frac{R(K)}{\mu_2(K)^2\hat{\Psi}_4(g)}\right]^{1/5} \quad (10)$$

Assuming the existence of the second derivative of the core function K(u) is verified, the limits of an agnostic convergence are found by the following algorithm:

1. Converting the image to gray and adding noise to the image calculate the standard deviation of the image.
2. Dissociate the original image into n_p sub-images.

3. Through Cartesian coordinates $I_k(i,j), k = 1, \dots, n_p$ which represents the density of the grayscale image unit for each given sub-image. The parameter of the width of the packets is calculated (Bandwidth Parameter) (44).
4. Calculate the core estimator and probability density function $\widehat{f}_n(x)$.
5. Calculate the variance for a function $\hat{f}_n(x)$ as follows: $\sigma_n^2(x) \simeq \frac{\hat{f}_n(x) \int K(u)^2 \, du}{nh_n}$.
6. Calculate the Unknown Confidence Limits of each Sub image $I_k(i,j), k = 1, \dots, r$:

$$p\left(\hat{f}_n(x) - Z_{\frac{\alpha}{2}} * \sigma_n(x) < I_k(i,j) < \hat{f}_n(x) + Z_{\frac{\alpha}{2}} * \sigma_n(x)\right) = 1 - \alpha$$

For each sub-image $I_k(i,j)$, if $I_k(i,j) < \hat{f}_n(x) + Z_{\frac{\alpha}{2}} * \sigma_n(x)$ *and* $I_k(i,j) > \hat{f}_n(x) - Z_{\frac{\alpha}{2}} * \sigma_n(x)$ then$I_k(i,j) = I_k(i,j)$, otherwise $I_k(i,j) = h\hat{f}_n(x)$

7. Reconstruct the previously processed image by creating the sub-images produced above. Both methods are compared with statistical measures, the average error square MSE and the image quality measure:

$$\mathrm{PSNR(X,Y)} = 10 * \log_{10} \frac{(\mathrm{MAX_{pixels}})}{(\mathrm{MSE(X,Y)})}$$

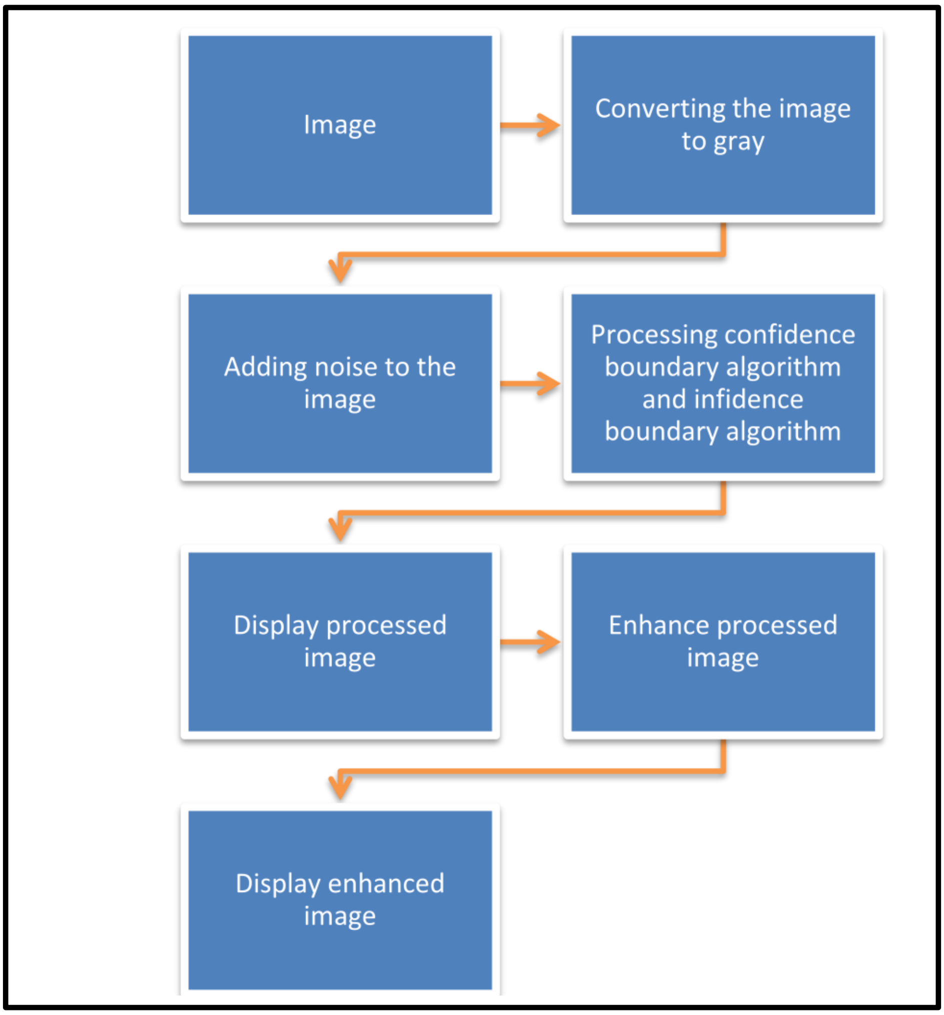

Fig. 1. Flow chart of the process of enhancing the image

IV. A practical aspect

To compare the parametric confidence limits method with the nonparametric confidence limits method for initial image processing, which was mentioned in the theoretical aspect, the algorithm was implemented on two different images using the MATLAB program, as shown in Figure 2.

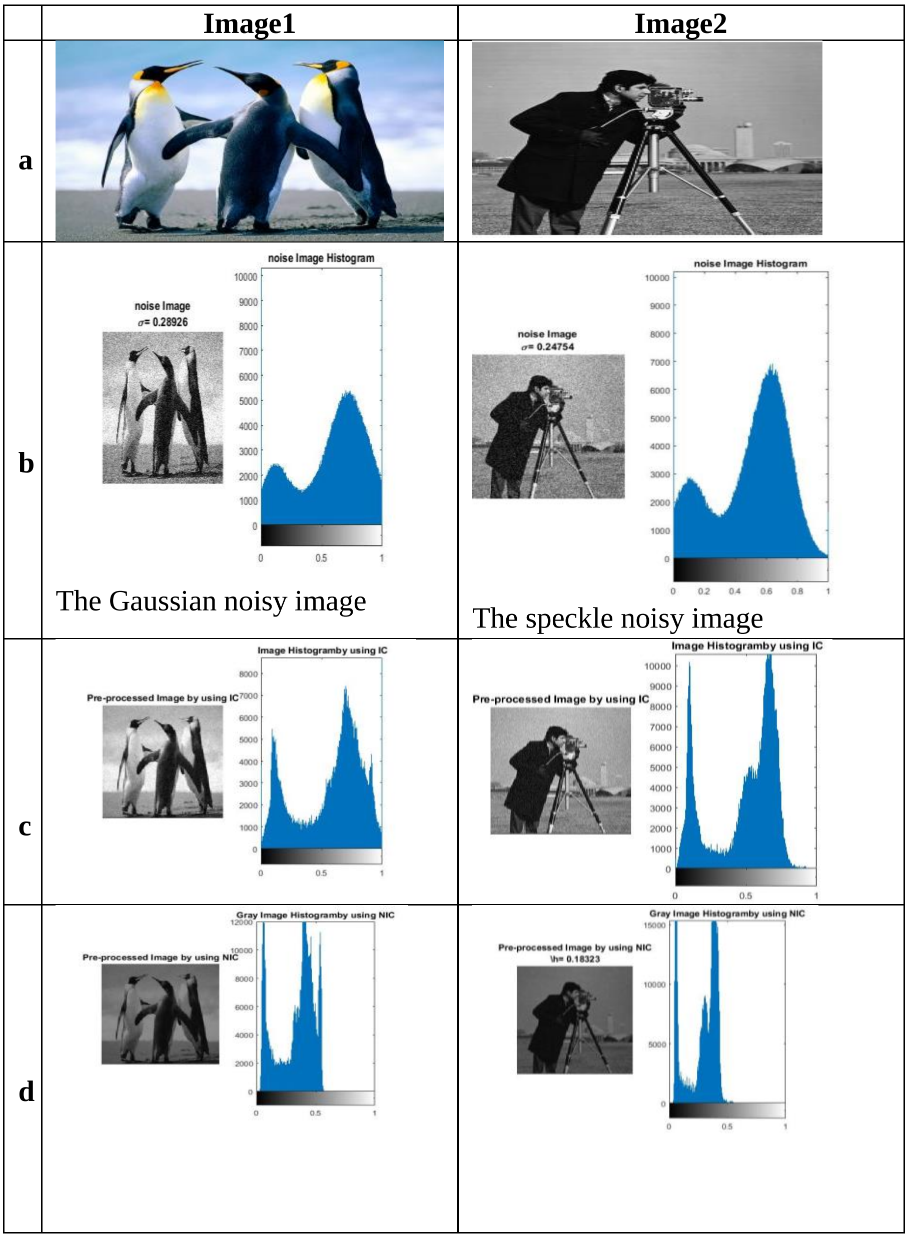

Fig. 2. (a) Original Images, (b) The original noisy images, (c) The pre-processed images by using our IC method, (d) The pre-processed images by using our NIC method.

In Figure 2, the two original images converted to grey, and a natural noise (Noise Gaussian), for the first image, with a value of 0.02 was added. In the second image, speckle noise is added, as shown in the image b. Following the application of the parametric confidence interval and nonparametric confidence interval algorithms, the two algorithms were able to eliminate noise from the two images, showing the most important features, and highlighting the boundary of parameters, as shown in image c. When compared with the MSE, the parametric confidence interval was found to be lower than the nonparametric confidence interval algorithm. Also, when using the image quality meter, it is found that the image extracted from the nonparametric confidence interval algorithm was found to be higher than the parametric confidence interval. The images produced by the method of using the nonparametric confidence interval give us better visual motivation because the parametric method was able to eliminate noise better than the method of the parametric confidence interval, as shown in Table 1.

Table 1 : Compared to remove PSNR by two methods (parametric Vs nonparametric confidence interval)

	Image (1)		**Image (2)**	
	MSE	PSNR	MSE	PSNR
IC	0.4060	52.0454	0.2900	53.5068
NIC	0.1370	56.7644	0.0984	58.2003

In Figure 3, the traditional histogram method was applied to improve the contrast of images extracted from the initial processing using both methods. Improved images were obtained that showed hidden features. However, the first enhanced image produced by the parametric confidence interval is more whiplash than the enhanced image produced by the nonparametric confidence interval. This is evident in the graph as contrast occupies a wide range of gradients, as presented in Figure 3.

In the initial processing using the parametric confidence interval, it is noted that the packet width parameter affects the operation of the algorithm. If the effect is too small to give a dark image. Therefore, it plays an important role in image processing. In this paper, the packet parameter was estimated using the thumb rule (Plug-In PI).

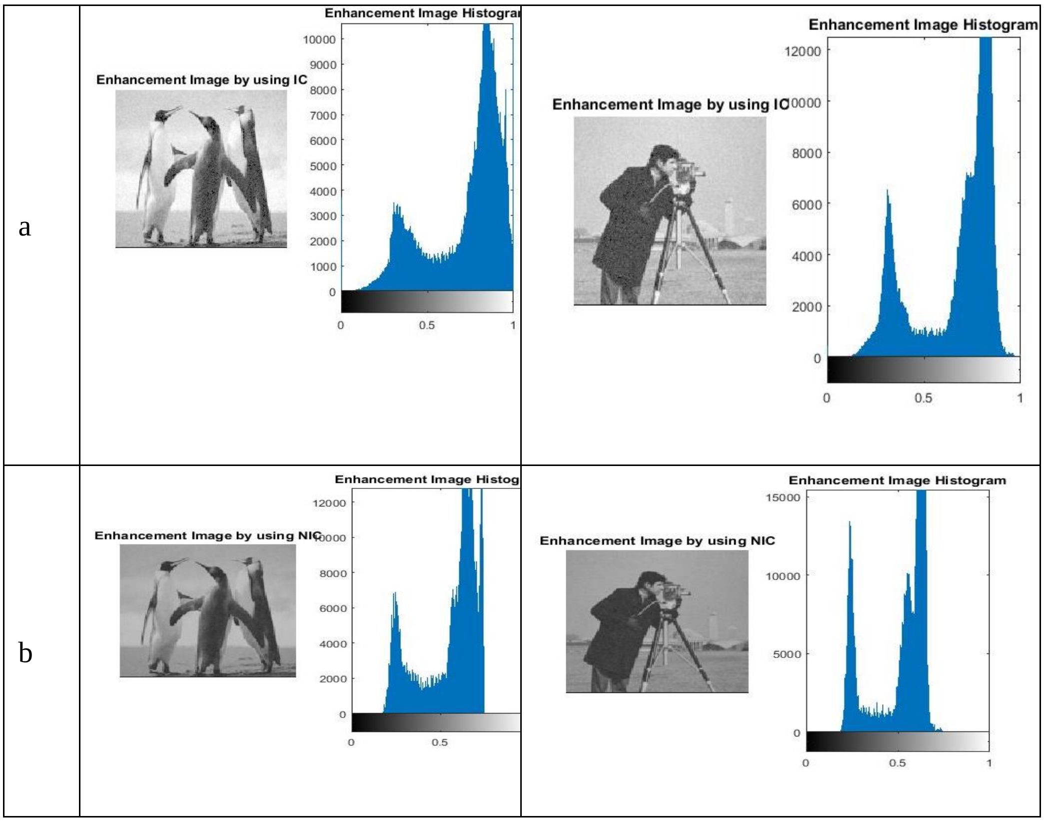

Fig. 3. (a) Enhancement Image by using IC, (b) Enhancement Image by using NIC

IV. Conclusion

In the digital world, digital image processing and enhancement are of great importance in multiple fields, including the scientific, geographic, and military fields. It has many applications in the scientific field, especially artificial intelligence, the development of robotic devices, and the analysis of data for images taken of Earth. This paper used two methods for removing the PSNR of images, which are the parametric and nonparametric confidence intervals. Therefore, the experiments show the two methods yielded satisfactory results in the initial process of removing noise, speckles, and natural noise from blurred images, and were shown to derive all the features of the images while eliminating any noise that might appear in the images. When compared using statistical scales, the nonparametric confidence interval method is better. Thus, the nonparametric confidence interval method removes noise from both images better, but the picture is darker than the parametric confidence interval image.

Conflict of Interest:

The authors declare that no conflict of interest in reporting the present article.

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