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A Comparison Study for the Effect of Applying Image Filters on Image's Statistical Distribution

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Abstract:

Image filters has taken attention last few years due to its importance in terms of image processing and applications. Applying image filters on images elements can be affected by the values of image parameters, which resulted from any processing tasks. By applying image filters, we can extent the image processing methods to present higher productivity. In this paper, we compare the effect of applying five image filters on the statistical distribution, which are (Laplacian, Differentiation, LOG, Sharpening, and Gaussian). Our method has been applied for a number of textural images (water texture, wool texture, and wood texture), the images has been divided for three groups according to the texture type. The result of our method proved that some of image filter affects the statistical distribution of image elements which are: (Differentiation, LOG, Sharpening) while other do not affect the parameter distribution (Laplacian, Gaussian). We evaluate our method by calculating the value of (MSE). The method opens the door in front of extending such technique with other image processing aspects.
Keywords: Images processing, Image filtering, Statistical distribution, Textural Images, Probability Density Function.

1. Introduction:

As commonly known, an image is composed from a number of characteristics and traits that can be extracted and employed in a wide range of applications (Pitas, 2000). For instance, medical image processing (Matthews, 2016; Semmlow & Griffel, 2014), where many information can be retrieved from and image to diagnose some medical issues. Images also implemented in terms of plant textures analysis and processing, where in images of plant can express many issues regrading to the plant case and the possibility of being infected by some plant diseases (Chen, 2015; Du & Sun, 2004). In addition to that, there are several other applications such as image localization, enhancing, compression, and information hiding.

For most images processing applications, there should be a number of processing steps that can contribute significantly in the results quality. One of the most common image processing techniques is image filtering (He, Sun, & Tang, 2013). Image filtering applications have witnessed wide spread since the emerging of digital image processing due to the wide canvas for filtering implementations in particular with the fields of enhancement, Compression, and classifications (Milanfar, 2013).

2. Related Work:

As previously mentioned, image filter have been widely employed with various image processing related scopes. In (Milanfar, 2013), the authors proposed an empirical and accessible image filtering frame work to clarify some filtering methods. The results of the proposed study led to analyze image filtering methods and their performance.

In (Nishikawa, Yoshida, Sugiyama, & Fujino, 2012), a robust image processing method has been presented. The method was composed of two major steps; firstly, a development of new image filter to detect the concrete cracks by utilizing genetic algorithms capabilities, and secondly, is about eliminating the noise from the captured images. The method has presented good performance in terms of cracks detecting in the concreted structures.

In (Christe, Vignesh, & Kandaswamy, 2012), the authors implement an image filtering for MRI images along with tumor characterization. The study present an efficient architecture for multiple filters form MRI images. The method results can reduce the consumed processing resources and enhance the usability. (Shrivakshan & Chandrasekar, 2012) presented a comparison study for different image filters by determining images edges. The method has been implemented form sample of shark images. The results have shown that the method can successfully implemented with images comparisons techniques.

A research presented by (Mittal & Dubey, 2013) analyzes the response images of (MRI) using the morphological network analyses for a number of bones images. The outcomes of the research stated that the method is highly beneficial in terms of diseases detection and diagnoses. Another study for image filtering has been presented in (Rani, 2013). The author presented a method for image filtering and noise reduction by implementing various noise reduction techniques. The presented method resulted plausible performance.

There are much more studies have discussed the importance of image filtering, in our study, we present image filtering form another point of view, which in the statistical distribution of image features and how it influence the results by applying different image filters. Our method discuss those features due to the importance and significance in terms of quality and information retrieved

3. Image Filters:

As commonly known, digital image is no more than two-dimensional array (m * n) of pixel which is the smallest part of any image, and accordingly (n) represents the number of pixel rows, while (m) denotes the number of columns. Thus, implementing and processing on the image to achieve a specific task (enhancement, rotation, and so on.) requires an application of a particular filter which also represented by a new array in order to come out with the desired results. In addition to that, the required filter should have the same size for both rows and columns, furthermore, those dimensions must be an odd numbers in order to enable finding the centered element (Figure(1)) (Li, Zheng, Zhu, Yao, & Wu, 2015).

A	*B*	*C*
D	*E*	*F*
G	*H*	*I*

Figure (2): A Sample of image filter

While the image elements and its closest adjacent ones can be explained briefly in (Figure 2), where each element hast its own position in addition to the neighbors.

f(x-1, y-1)	f(x-1, y)	f(x-1, y + 1)
f(x, y-1)	f(x, y)	f(x, y + 1)
f(x + 1, y-1)	f(x + 1, y)	f(x + 1, y + 1)

Figure (3): Image element distribution

Image filters vary in accordance to their sizes and contents, which represent the numerical parameters. So that the desired results of any method of filter application, depend mainly on those parameters (i.e. size and consents). The resulted image element of any processing is represented by the following formula:

$$P_{ij} = \sum_{v=0}^{k-1} \sum_{w=0}^{L-1} u_{vw} h_{vw} \quad \dots\dots\dots (1)$$

Where:

- (P_{ij}) Represents the image element for the new image according to the location (row (i), and column (j)).
- (u_{vw}) Represents the factor of the filtered image element, according the row (v) and column (w).
- (h_{vw}) represent the image element for the new image depending on row (v) and column (u).

Applying any image filter will definitely require calculating all the values of image's parameters, the following formulas can be employed to find such parameters:

- The first and second derivative for (x):

$$\frac{\partial f(x,y)}{\partial x} = f(x+1,y)\text{-}f(x,y) \dots\dots\dots (2)$$

$$\frac{\partial^2 f(x,y)}{\partial^2 x} = f(x+1,y)\text{-}f(x\text{-}1,y)\text{-}2f(x,y) \dots\dots\dots (3)$$

- The first and second derivative for (y):

$$\frac{\partial f(x,y)}{\partial y} = f(x,y+1)\text{-}f(x,y) \dots\dots\dots (4)$$

$$\frac{\partial^2 f(x,y)}{\partial^2 y} = f(x,y+1)\text{-}f(x,y\text{-}1)\text{-}2f(x,y) \dots\dots\dots (5)$$

- Finding the image filter parameter:

$$\nabla^2 f(x,y) = \frac{\partial^2 f(x,y)}{\partial^2 x} + \frac{\partial^2 f(x,y)}{\partial^2 y} \dots\dots\dots (6)$$

- By substitute each of (3,5) formulas by the formula(6), we get the following formula:

$$\nabla^2 f(x,y) = [f(x+1,y) + f(x\text{-}1,y) + f(x,y+1) + f(x,y\text{-}1)\text{-}4f(x,y)] \dots\dots (7)$$

- Hence, with formula (7), we can build an image filter to be more like the illustrated in (Figure (3)). Accordingly, the rest of image elements can be found.

0	1	0
1	- 4	1
0	1	0

Figure (4): The image filter parameters according to the extracted parameters

In our paper, we employ five different image filters; Table (1) shows the parameters of the five image filters implemented in our paper

	Column filters parameters														
	Laplacian (P_1)			Differentiation (P_2)			LOG (P_3)			Sharpening (P_4)			Gaussian (P_5)		
Row filter parameters	1	-2	1	-1	-2	-1	0	-1	0	-1	-1	-1	1	2	1
	-2	7	-2	0	0	0	-1	4	-1	-1	9	-1	2	4	2
	1	-2	1	1	2	1	0	-1	0	-1	-1	-1	1	2	1

Table (1): Five Image Filters Used in Our Paper

4. STATISTICAL DISTRIBUTIONS:

In the real situations, different phenomenon can be represented statistically according to its own distribution, hence, knowing the statistical distribution enable the behaviour expectation that belongs to particular phenomenon, and eventually identify it. The statistical distribution for any given phenomenon can be represented by several functions, which can be described as follows:

4.1 Probability Density (Mass) Function

which represents the probability value that reflects the probability for any value of the statistical variable, so that, the probability mass function (PMF) denotes the value for each discrete variable, while the probability density function (PDF) denotes the probability for each series of continuous variable. The formulas (8, 9) represent the both mentioned functions.

$$\sum_{a=-\infty}^{\infty} P(x) = 1 \qquad P(x) \geq 0 \ldots\ldots\ldots (8)$$

$$\int_{-\infty}^{\infty} f(x) = 1 \qquad \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

The statistical distribution for the random variable has a number of parameters that must be estimated, since whole functions identification requires finding the value of estimator for the parameter distribution. There are number of methods can be used to do this task, such as Maximum Likelihood Estimation Method (MLEM), Moment Estimation Method (MEM), and Shrinkage Estimation Method (SEM) (Hogg & Craig, 1995).

MLEM is considered as one of the most common method that have been widely used in terms of statistical distribution (Wood, 2011). The method can be abstracted as follows:

– Let (x) depicts (n) of observations ($x_1, x_2, x_3, \ldots\ldots\ldots x_n$), where each value of ($x$) has its own identical independent distributed. Based on one of the distributions ($f(x_i/\vartheta)$), therefore, we can find the MLE throughout the following formulas:

$$f(x_1, x_2, x_3, \ldots, x_n/\vartheta) = \prod_{i=1}^{n} f\left(\frac{x_i}{\vartheta}\right) \qquad \ldots\ldots\ldots (10)$$

$$\prod_{i=1}^{n} f(x_i/\vartheta) = f\left(\frac{x_1}{\vartheta}\right).f\left(\frac{x_2}{\vartheta}\right)\ldots f\left(\frac{x_n}{\vartheta}\right) \qquad \ldots\ldots\ldots (11)$$

$$L(\vartheta; x_1, x_2, x_3, \ldots, x_n) = f\left(x_1, x_2, x_3, \ldots, \frac{x_n}{\vartheta}\right) \qquad \ldots\ldots\ldots (12)$$

$$L(\vartheta; x_1, x_2, x_3, \ldots, x_n) = \prod_{i=1}^{n} f(x_i/\vartheta) \qquad \ldots\ldots\ldots (13)$$

$$Ln\big(L(\vartheta; x_1, x_2, x_3, \ldots, x_n)\big) = \sum_{i=1}^{n} Ln\left(f\left(\frac{x_i}{\vartheta}\right)\right) \qquad \ldots\ldots\ldots (14)$$

By finding the derivative for the formula (14) and set it to (0), we get the MLE value as follows:

$$\partial\big(Ln\big(L(\vartheta; x_1, x_2, x_3, \ldots, x_n)\big)/\ \vartheta\big) = 0 \qquad \ldots\ldots\ldots\ldots (15)$$

4.2 Chi-Square Test:

Is one of the well-known statistical tests that mainly used by to answer different statistical hypothesis (H_1, H_0) (Satorra & Bentler, 2001). The value of Chi-Square test is calculated by employing the following equation:

$$\chi^2 = \sum_i \frac{(O_i - E_i)^2}{E_i} \quad \dots\dots\dots (16)$$

Where:

- (O_i) denotes a specific observation.
- (E_i) denotes the expected values

The average of differences squares is calculated through the following formula:

$$MSD = \frac{\sum_{i=1}^{k}[f_{1i} - f_{2i}]^2}{k} \quad \dots\dots\dots\dots\dots (17)$$

Where:

- (f_{1i}) is the first frequency distributions.
- (f_{2i}) is the second frequency distributions.

5. THE METHODOLOGY AND IMPLEMENTATION

For any research, there should be a number of specific task to be implemented and evaluated. As mentioned earlier, in our paper we compare the statistical distribution for the processed images after applying different image filter, and then evaluate the outputs. The block diagram for our method is illustrated in (Figure (4)).

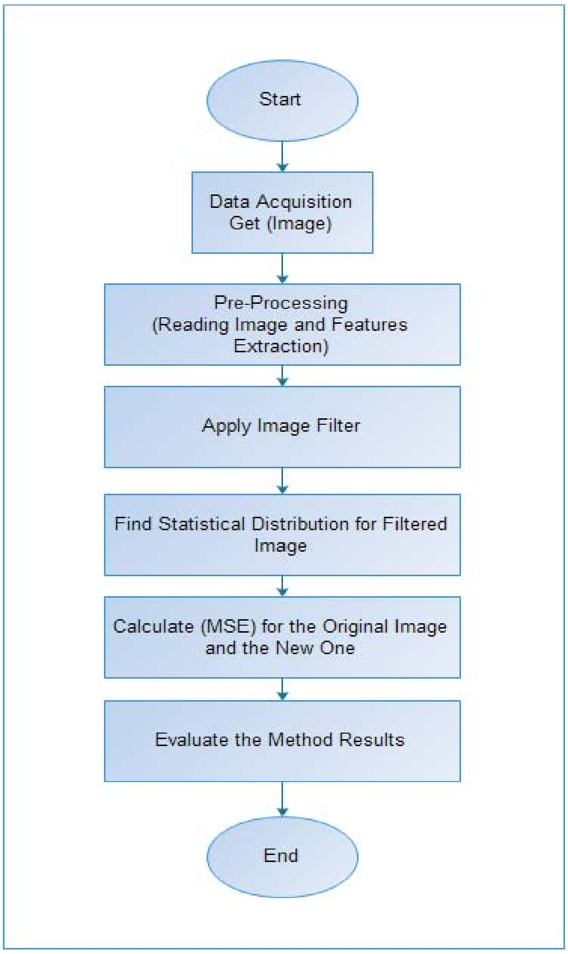


Figure (5): Research Methodology Block Diagram

As shown in figure (4), our method composed of number of specific tasks starting with getting the data to be processed. The paper data is consisting of (6) Textural Images (TI) with different textures (water texture, wool texture, and wood texture), as stated in (Table (2)). Each image represented by a particular array of image elements, so that (TI_i) represent a particular image, where *(i = 1, 2 3, 4, 5, 6)*. Then the images is divided into (3) main groups according to the texture type (*U* for water texture, *S* for wool texture, and *W* for wood texture), each texture type has (3) images.

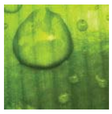
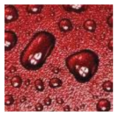
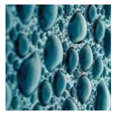
		Image Groups		
		T1	T2	T3
Texture Type	U			
	S			
	W			

Table (2): The Sample of Image Groups

To perform the processing tasks, we utilize the Matlab as a programming tool to process and evaluate the method presented. For processing, we implement the Chi-Square test (χ^2) for the input images to find the statistical distribution and the main parameters. Table (3) shows the values of the statistical distribution and the value of (χ^2) for the textural images.

Textural Images		Parameters of Distribution		χ^2	Distribution fitting
		$\hat{a}$	$\hat{\beta}$		
U	1	0.14612	0.00000	16.06100	Pareto
	2	0.00384	0.00710	44.07900	Inv. Gaussian
	3	2.60790	73.47200	15.18000	Pearson
S	1	0.00436	0.00164	16.61600	Cauchy
	2	0.00384	0.00284	2.01580	Error
	3	0.00175	0.00943	13.83100	Uniform
W	1	0.58652	0.00072	15.45900	Frechet
	2	0.68931	0.00130	25.12700	Frechet
	3	0.00421	0.00174	15.96600	Cauchy

Table (3): The Parameters Estimation for Each Textural Group

Form the previous table, it can be clearly seen that, the suitable distribution for the image texture form type *(W)* is mostly from the type (Frechet) with almost approximate values of ($\hat{a}$) for the whole

distribution. This is due to the stability of the statistical distribution although the texture has changed; nevertheless, the texture size is big.
We also can see that the other texture *(U)* has earned different statistical distributions and this is because of the difference in the texture, even when the colours are more consistent.

After applying the image filters mentioned in (Table (1)) for all images in the dataset, we get the results illustrated in (Table (4)), which describes mean squares differences for image elements.

Textural		MSD						
		P_1 [(1)]	P_2	P_3	P_4	P_5	Max	Min
U	1	5.42E-12	1.34E-09	9.25E-11	3.35E-10	5.78E-08	5.78E-08	5.42E-12
	2	1.27E-10	3.92E-09	2.71E-09	9.76E-09	5.36E-08	5.36E-08	1.27E-10
	3	1.09E-11	7.08E-10	4.49E-10	1.81E-09	5.53E-08	5.53E-08	1.09E-11
S	1	1.66E-11	3.46E-10	1.16E-09	4.70E-09	5.75E-08	5.75E-08	1.66E-11
	2	1.59E-11	3.48E-10	6.75E-10	3.10E-09	5.68E-08	5.68E-08	1.59E-11
	3	9.68E-11	2.32E-09	1.40E-09	7.72E-09	5.76E-08	5.76E-08	9.68E-11
W	1	1.27E-10	1.37E-09	4.20E-09	1.20E-08	5.77E-08	5.77E-08	1.27E-10
	2	1.07E-11	7.50E-10	1.05E-09	5.80E-09	5.74E-08	5.74E-08	1.07E-11
	3	4.59E-11	2.92E-10	1.63E-09	9.53E-09	5.63E-08	5.63E-08	4.59E-11
Max		1.27E-10	3.92E-09	4.20E-09	1.20E-08	5.78E-08	5.78E-08	
Min		5.42E-12	2.92E-10	9.25E-11	3.35E-10	5.36E-08		5.42E-12

Table (3): Mean Squares Difference for Original and Filtered Images

From the above table, we can notice that the values of mean squares for each pair of images - Original one and filtered one– has been affected noticeably, where the smallest differences belongs to the filter (P_1), in addition, the largest differences belong to the filter (P_5).

By comparing the results for the rest of filters (P_2,P_3, P_4), we note that the result of the filter (P_2) with (P_3) has the biggest amount of differences for the texture groups (W, U), while the results were mostly at the opposite direction according to the texture group (S). This means the results of the filtering processes are influencing by the image texture type and can indicate the texture differences. Figures (5) and Figure (6) illustrate the overall results.

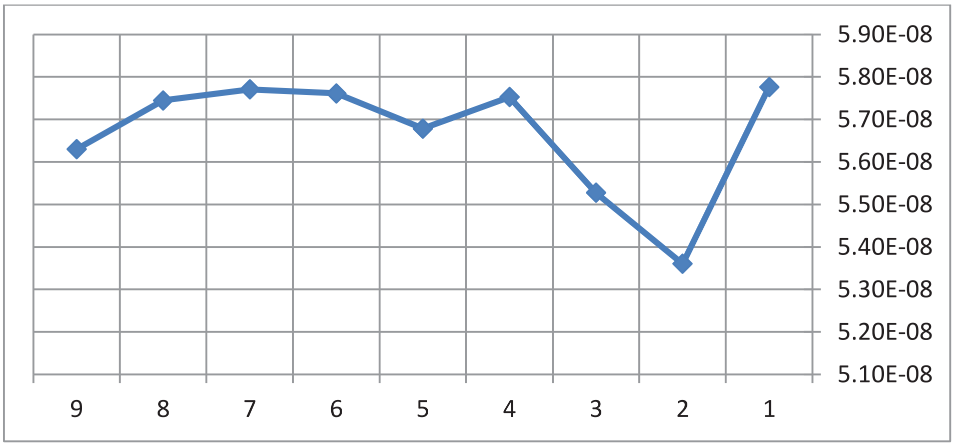


Figure (6): The Biggest Mean Squares for all Image Textures

1- See table (1) for filter names

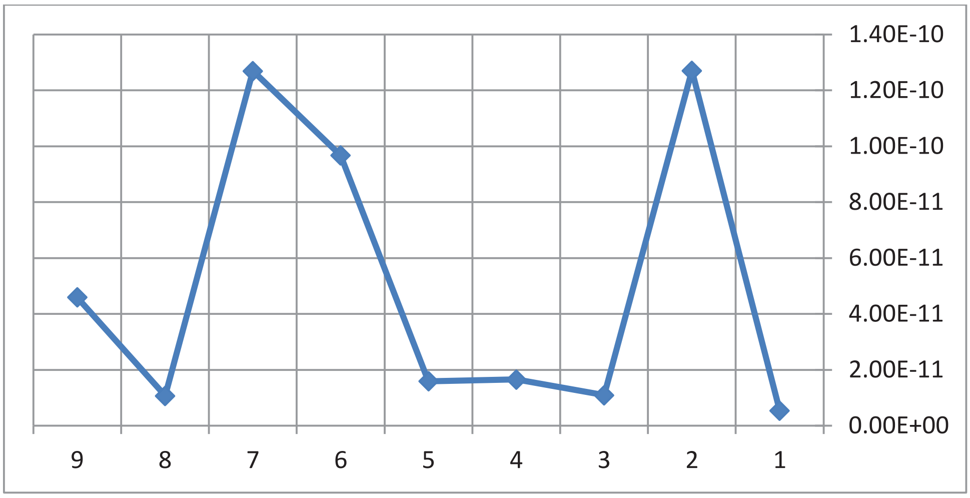


Figure (7): The Smallest Mean Squares for all Image Textures

We also can note that the textures with high level of variety in terms of colours and contents, presented bigger values regardless the filter type. And this means that the textural images has fluctuated performance according to the distribution values. Table (5) shows the distribution of textural images after applying the filter, which states the biggest mean squares differences between the original and filtered images, where the blank cell means that the image filter is not applicable for such image where it causes fluctuated values.

Textural Images		Parameters of Distribution		χ^2 Test	Distribution fitting
		$\hat{\alpha}$	$\hat{\beta}$		
U	1	-	-	-	No fit
	2	0.00421	0.91171	17.609	Gamma
	3	0.00408	0.9413	29.089	Gamma
S	1	-	-	-	No fit
	2	7.6500E-6	1.5300E-5	52.17	Cauchy
	3	-	-	-	No fit
W	1	-	-	-	No fit
	2	5.0546E-7	1.2586E-6	221.85	Pareto
	3	0.00401	0.95851	69.948	Gamma

Table (4): The Statistical Distribution after Processing

6. CONCLUSIONS:

According to table (4), it can be seen that the distributions for four textures have been totally removed without suggesting any other distribution. While the other textures keep changing from distribution to another. Here we can say that the image processing using filters produces modifications in the characteristics in addition to the statistical distributions.

Furthermore, the processed images can be easily discovered after performing any modifications by comparing the original one with the processed one; however, this can preserve the any image ownership after being published. Moreover, this process can be implemented in terms of forgery, fraud detections, and steganography and much more aspects. When selecting the textural images to be processed using any given filter, it can be shown that there is a significant effect on statistical distribution stability, and this issue can be used in terms of pattern recognition fields.

After performing the method, we formulate a number of conclusions as follows; the image filters are beneficial techniques especially when impended with high level of accuracy. In addition, the statistical distribution of any image parameters mainly depends on the texture type. Furthermore, some filters have no significant influence when applied to specific images, where some filters are sensitive against the statistical distribution as well as the texture type. For future trends, the presented work can be implemented, and extended for different image processing aspects, such as pattern recognition, security, steganography, and so on.

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